ESSAYS ON APPLIED ECONOMICS AND ECONOMETRICS: DECADAL CLIMATE VARIABILITY IMPACTS ON CROPPING AND SUGAR-SWEETENED BEVERAGE DEMAND OF LOW-INCOME FAMILIES

A Dissertation

by

THEEPAKORN JITHITIKULCHAI

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Chair of Committee,	Ximing Wu
Co-Chair of Committee	Bruce A. McCarl
Committee Members,	David A. Bessler
	Marco A. Palma
	Ke-Li Xu
Head of Department,	Parr Rosson

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ABSTRACT

This dissertation examines the economic impacts of ocean-related climate variability on U.S. crops and the effect sweetened beverage taxes would have on beverage consumption among low income food assistance program participants. The first essay estimates the effect of decadal climate variability (DCV) on crop yield, output, and revenue distribution moments controlling for temporal and spatial heterogeneity. The second essay estimates a demand system for beverages and the consumption effects of taxes on sugar-sweetened beverages (SSB).

The DCV analysis endeavors to advance the literature by econometrically estimating the impacts of these climate phenomena on crops. The estimation is done developing an empirical model that combines the direct and indirect effects of DCV. The direct DCV effects are estimated with skew-normal regression, allowing effects on skewness. The indirect DCV effects on crops are passed through regional hydro-meteorological variables such as temperature, precipitation, drought, and rainfall intensity. This study provides evidence that DCV phase combinations are related to the regional changes in temperature, precipitation, and extreme events and that this alters crop yields, output, and revenue across the United States. In turn adaptations are examined and we find DCV information could help farmers profitably alter crop mixes.

For the sugar-sweetened beverage investigation this study examines the demand elasticities of beverage purchases among low-income households participating in federal food assistance programs. Using scanner data from a New England supermarket chain

with 3.8 million product-level purchases by over 47,000 households, we aggregate them by store level and month. We estimate a demand system model for eleven non-alcoholic beverages for different payment types. Our results suggest that an excise tax would be an effective means to reduce SSB consumption and increase healthier beverage purchases among low-income households.

DEDICATION

To those most suffering people and for peace throughout the world

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NOMENCLATURE

BLS	Bureau of Labor Statistics
CSD	Carbonated soft drinks
DCV	Decadal climate variability
EBT	Electronic Benefit Transfer
ENSO	El Niño-Southern Oscillation
GLM	Generalized linear model
GLS	Generalized least square regression
MRB	Missouri River Basin
NASS	National Agricultural Statistics Service
NAO	North Atlantic Oscillation
NCDC	National Climatic Data Center
NLSUR	Nonlinear Seemingly Unrelated Regression model
NOAA	National Oceanic and Atmospheric Administration
ONI	Oceanic Niño Index
PDSI	Palmer Drought Severity Index
PDO	Pacific Decadal Oscillation
QUAIDS	Quadratic Almost Ideal Demand System model
RTD	Ready-to-drink
SNAP	Supplemental Nutrition Assistance Program

SSB	Sugar-sweetened beverage
SST	Sea-surface temperature
TAG	Tropical Atlantic Gradient
USDA	US Department of Agriculture
WIC	Special Supplemental Program for Women, Infants, and Children
WPWP	West Pacific warm pool
ZIP	Zero-inflated Poisson regression model

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CHAPTER I

INTRODUCTION

This dissertation contains two essays with a common theme on applied econometrics and then economic implications for the value of government actions. Chapter II presents the results of a study on the yield and economic effects of decadal and annual climate variability and discusses the value of variability information in crop mix adaptation. Chapter III presents the results of an investigation on the demand for sugar-sweetened beverages (SSBs) by low-income households participated in the Special Supplemental Program for Women, Infants, and Children (WIC) benefits and the estimated impacts of tax policy on reducing SSBs consumption.

More specifically Chapter II presents the results of a study on the effects of decadal climate variability (DCV) on U.S. crop yield distributions and then investigates some adaptation possibilities given DCV information. DCV identifies persistent ocean phenomena existing on at least inter-decadal time scales (Mehta 2008 and Wang and Mehta 2008; Murphy et al. 2010; Mehta et al. 2013b). There are three forms of DCV examined herein: the Pacific Decadal Oscillation (PDO) (Mantua et al. 1997; Mantua 1999; Ting and Wang 1997; Smith et al. 1999; Mantua and Hare 2002), the Tropical Atlantic Sea-surface Temperature Gradient (TAG) (Mehta 1998; Hurrell et al. 2001), and the Western Pacific Warm Pool Sea Surface Temperature (WPWP) (Wang and Enfield 2001; Wang et al. 2006; Wang and Mehta 2008). Joint phase combinations of these DCV phenomena have been found to impact drought and extreme weather events plus shorter periodic ocean phenomena, (e.g. El Niño-La Niña, hurricanes and other tropical cyclones, extreme precipitation or heat events) as reviewed by Latif and Barnett (1994) and Mehta et al. (2013b). Researchers have found that DCV associated variations in major ocean long run temperature patterns have been associated with multiyear to multi-decadal droughts plus changes in precipitation patterns (Latif and Barnett 1994; Mantua et al. 1997; Zhang et al. 1997; Mantua 1999; Schwierz et al. 2006; Wang and Mehta 2008; Meehl et al. 2010; Murphy et al. 2010; Mehta et al. 2011; Mehta et al. 2012; and Mehta et al. 2013b)

Studies have also found that shorter run ocean phenomena such at El Niño-Southern Oscillation (ENSO) events influence crop yields (Adams et al. 1990; Adams et al. 1995; Mjelde and Griffiths 1998; Solow et al. 1998; Adams et al. 1999; Chen, McCarl, and Schimmelpfennig 2001) and weather over land such as heavy rain, flooding, severe drought, and hurricanes (Bouma et al. 1997; Dilley and Heyman 1995; Maybank et al. 1995; Pielke and Landsea 1999; Chappell 2000; Rajagopalan et al. 2000; and Hallegatte et al. 2011). Bove et al. (1998), Solow et al. (1998), and Adams et al. (1999) explore the potential economic impacts of knowledge about these phenomena and their yield effects

Given this background the first question investigated by this dissertation explores how DCV phenomena affect US major crop yields, outputs, and revenues on their distributions across a number of locations. We also examine possibilities of agricultural adaptation given DCV information.

Chapter III describes a demand analysis and associated analysis of tax impacts examining beverage purchases by low-income households for sugar-sweetened beverages (SSB). SSBs have been shown to be a contributor to obesity and the costs obesity imposes (Malik et al. 2006, Finkelstein et al. 2009).

Schwartz and Friedman (2012) argued that SSBs should be the primary focus of obesity prevention campaigns as research linking SSBs to obesity and other negative health outcomes is stronger than for any other single beverage or food. As low-income populations are most affected by excessive SSB consumption and diet-related illnesses (Brownell et al. 2009), tax policy that shifts intake from SSBs to non-caloric or low-calorie beverages would particularly benefit these economically-disadvantaged groups. New tax revenue could be further directed towards improving nutrition of low-income families.

To the best of our knowledge, there are no SSB demand analysis studies looking at effects of beverage prices on SSB consumption in low-income households that use food assistance benefits. Thus, our second research question in this dissertation will involve the comparison of the responsiveness of the Supplemental Nutrition Assistance Program (SNAP) and WIC households to SSB price changes. We will also investigate the impacts from SSB taxes on reducing SSB purchases and caloric consumption.

Objectives

This dissertation will pursue two economic analysis objectives:

- To understand how DCV and other climate and weather factors have influenced distributions of major crop yield, output, and revenue, and possibilities for crop mix adaptation
- To understand own-price and cross-price elasticities of SSB purchases among low-income families, in particular food assistance program participating households, and how SSB tax policy could affect their beverage purchases

Plan of Dissertation

In pursuing the above objectives, this dissertation contains four chapters. This introduction is Chapter I. Chapter II reports the DCV investigation. Chapter III reports the SSB demand investigation. Chapter IV summarizes findings and provides overall concluding comments.

CHAPTER II

DECADAL CLIMATE VARIABILITY IMPACTS ON CROPPING

Society has become aware of systematic variations in weather[1] due to ocean phenomena. Economic evaluation of the effects of information on ocean-related climate variation has been the subject of economic research in a number of settings including agriculture as reviewed in Mjelde and Griffiths (1998) and Chen and Chang (2005). The El Niño Southern Oscillation (ENSO) has been found to have predictable influences on weather and crop yields in many locations (Hastenrath (1995), Solow et al. (1998), Adams et al. (1999), Phillips et al. (1999), Smith et al. (1999), Chen and McCarl (2000), Wang and Fu (2000), Chen et al. (2001), Chen et al. (2004), Chen et al. (2005), Kim and McCarl (2005), Hennessy (2009), Tack et al. (2012), Tack and Ubilava (2012), and Mendez (2013) among many others).

However, while ENSO has received a lot of attention, there are a number of other ocean related phenomena. In particular, Ting and Wang (1997), Smith et al. (1999), Hurrell et al. (2001), Kushnir et al. (2001), and Wang and Mehta (2008) review a number of such phenomena and their weather implications. Studies have also been done by Hurrell et al. (2001), Kim and McCarl (2005), and Mehta et al. (2012) on crop yield effects of other ocean phenomena.

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[1] Throughout, "weather" refers to temperature, precipitation, drought, and weather intensity (numbers of days in the month with temperature greater than or equal to 90 Fahrenheit and with precipitation greater than or equal to 1.0 inch) at a given time and place. "Ocean phenomena" refer to natural ocean variations that have been found to affect weather over periods of time which are DCV and ENSO.

One ocean phenomena that has not been subject to much economic analysis is decadal climate variability (DCV) which identifies persistent ocean phenomena existing on at least inter-decadal time scales (Wang and Mehta 2008 and Mehta 2008; Murphy et al. 2010; Mehta et al. 2013b). DCV conditions have been found to impact drought and extreme weather events plus shorter period ocean phenomena, (e.g., El Niño-La Niña, hurricanes and other tropical cyclones, extreme precipitation or heat events) as reviewed by Latif and Barnett (1994) and Mehta et al. (2013b). Also DCV phenomena have been argued to affect agriculture, water supply, drainage, fisheries, wildlife and river- and reservoir-based recreation among other activities (Mehta et al. 2013a; Mehta et al. 2013b).

This paper explores how DCV phenomena affect United States crop yields, outputs, and revenues, plus their distributions. Specifically, we do an econometric investigation on how DCV phenomena affects crop yield distributions across the US. We also examine total production and revenue effects. In doing this we do a statistical analysis as done in others (Solow et al. 1998; Phillips et al. 1999; Chen and McCarl 2000; Chen et al. 2001, 2005; and Mehta et al. 2012). After this we explore crop mix adaptation possibilities given DCV information.

Background: Decadal Climate Variability

Natural variability of the climate system at decadal to multidecadal timescales has been studied (Latif and Barnett 1994; Mantua et al. 1997; Zhang et al. 1997; Schwierz et al. 2006; Wang and Mehta 2008; Meehl et al. 2010; Murphy et al. 2010; Mehta et al. 2011; Mehta et al. 2012; and Mehta et al. 2013b among others). Their main findings have been that major ocean long run temperature patterns have been associated with multiyear to multi-decadal droughts plus changes in precipitation patterns.

There are three forms of DCV that will be examined in this study. These are the Pacific Decadal Oscillation (PDO) (Mantua et al. 1997; Ting and Wang 1997; Smith et al. 1999; Mantua and Hare 2002), the Tropical Atlantic Sea-surface Temperature Gradient (TAG) (Mehta 1998; Hurrell et al. 2001), and the Western Pacific Warm Pool Sea Surface Temperature (WPWP) (Wang and Enfield 2001; Wang et al. 2006; Wang and Mehta 2008).

The PDO is a Pacific ocean phenomenon that is characterized by two phases: warm and cold. These are identified based on sea surface temperature (SST) anomalies in the North Pacific Ocean (Mantua et al. 1997; Zhang et al. 1997). The PDO phase combinations have persisted for 20-to-30 years in the 20th century (Mantua and Hare 2002). The PDO influences weather through heat transfer between the overlying atmosphere and the Pacific Ocean. In turn, this influences winds in the lower troposphere; and is associated with periods of prolonged dryness and wetness in the western United States and the Missouri River Basin (Murphy et al. 2010). There is evidence of PDO impacts in the Southern Hemisphere, over the mid-latitude South Pacific Ocean, Australia, and South America (Mantua and Hare 2002).

The TAG is a long-lived El Niño-like pattern of Atlantic water characteristics that persists for 12-13 years. It also has two phase combinations, positive and negative. The TAG is identified through Atlantic SST variations in the cross-equatorial dipole pattern (Mehta 1998). The TAG has been found to be associated with variability in many ocean and atmospheric items, such as heat transferred between the overlying atmosphere and the Atlantic Ocean; winds in the lower troposphere; and rainfall in the southern, central, and mid-western United States (Murphy et al. 2010).

The WPWP is a western pacific phenomenon and is associated with changes in ocean temperature and in turn with anomalies in levels of temperature and precipitation which changes on a 10-15 year period. It is a region of sea surface temperatures (SST) warmer than 28.5°C extends from the eastern North Pacific to the Gulf of Mexico and the Caribbean on the west of Central America, then, at its peak, expands to the tropical waters to the tropical North Atlantic on the east (Wang and Enfield 2001). It again has two phase combinations. The WPWP exerts an influence on weather over the Great Plains with the positive phase combination is associated with precipitation and temperature variation in the Great Plains and Western Corn Belt (Wang and Mehta 2008).

Background: Analysis on Crop Yields and Weather

A number of studies have addressed the effects of climate on crop yields and weather. Below we review those that focus on ocean phenomena and climate change. We will also review studies that analyze higher order moments of crop yield distributions.

Impacts of Ocean Phenomena on Weather

A number of other studies have addressed weather effects of ocean phenomena. Mantau et al (1997) found that PDO affects coastal sea and continental surface air temperatures from Alaska to California. They also found it affects stream flow in major west coast river systems. Wang et al. (2012) found US summer precipitation and surface air temperature anomalies during the evolving phase of El Niño [2] and during summers following the peak phase of the winter El Niño. Wang and Fu (2000) found an association between El Niño SSTs and winter anomalies in precipitation and surface temperature over the North Pacific and North America. Wang and Ting (2000) found a strong but geographically differentiated association between precipitation variability in the southeastern and northwestern United States and Pacific SST anomalies. Ting and Wang (1997) found that year-to-year fluctuations in summertime precipitation over the US Great Plains were significantly correlated with tropical and North Pacific sea surface temperature (SST) variations. Wang et al (2010) found that increases in Southeast summer precipitation variability were primarily associated with SST warming in the Atlantic and also with SST variability across the equatorial Atlantic. Chou and Lo (2007), Cai et al. (2010), and Afzaal et al. (2013) found asymmetric ENSO effects on precipitation.

Méndez and Magaña (2010) found SST anomalies in the North Pacific Ocean led to positive anomalies in the standardized precipitation index over the northeastern United States. They suggest this tended to weaken the intensity of the 1950s drought over this region. The Pacific SST was found to alter North American precipitation data by Meehl et al. (2010). In particular, they found increases in Pacific SST were associated with increased precipitation in northern North America and the Mississippi basin plus

[2] See detailed discussion in Cane and Zebiak (1985), Trenberth and Stepaniak (2001), and Yu and Kim (2010).

reduced precipitation over the southwest and eastern United States (Meehl et al. 2010). Across these studies the evidence shows the large-scale interdecadal variability of climate forcing from North Atlantic Oscillation (NAO), PDO, and WPWP influences the precipitation variability on Great Plain and Midwestern in addition to effects from ENSO-precipitation variability (Mehta et al. 2011).

Mehta et al. (2011) found DCV phenomena have significant impacts on the hydrometeorology of the Missouri River Basin. They found that PDO, TAG, and WPWP phases were associated significantly with decadal precipitation and temperature variability plus drought, flood, or neutral hydro-meteorological conditions. They indicate that consideration of the DCV phenomena explains 60% to 70% of the total variance in annual precipitation and water supply. They also found a large influence on maximum and minimum temperatures. Their analysis of hydro-meteorological records indicated that decadal droughts and wet spells were correlated with DCV phenomena phase combinations. In particular, they concluded that (1) during the positive PDO phase (PDO+), precipitation was above average almost everywhere and temperatures were generally lower than average; (2) in positive TAG+ phases, precipitation was found to be below average almost everywhere and temperatures increased almost everywhere; and (3) WPWP impacts varied by subarea in the Basin and had less influence than PDO and TAG.

Wang et al. (1999) developed a method for seasonal prediction of US precipitation based on tropical Pacific sea surface temperature (SST) anomalies. Significant predictability of summer precipitation was found over the Northern Plains and Atlantic States during El Niño phases, while in the Midwest summer precipitation predictability was found during the La Niña phase. The El Niño phase is associated with above normal summer precipitation in the Northern Plains and Midwest but below normal precipitation in the Atlantic States. Significant predictability was also detected for winter precipitation over the Gulf Coast States, the Southern Plains and California. Higher precipitation events in those regions are generally associated with the El Niño phase of ENSO.

Impacts of Ocean Phenomena on Crop Yields

Studies have found that ocean-related phenomena influence weather over land and in turn crop yields. Heavy rain, flooding, severe drought, and hurricanes have also been found to be associated with ENSO phases (Dilley and Heyman 1995; Maybank et al. 1995; Bouma et al. 1997; Pielke and Landsea 1999; Chappell 2000; Rajagopalan et al. 2000; and Hallegatte et al. 2011). In turn ENSO events have been found to have impacts on US agricultural regional crop yields. (Mjelde and Griffiths 1998; Solow et al. 1998; Adams et al. 1999; Chen, McCarl, and Schimmelpfennig 2001). Others (Bove et al. 1998, Solow et al. 1998, and Adams et al. 1999) have studied the potential agricultural economic consequences of knowledge about these phenomena and their yield effects.

Adams et al. (1999) estimated the agricultural economic consequences of ENSO events using a stochastic economic model of the US agricultural sector. They found that the total effects of both extreme ENSO phases are negative for US agriculture and consumers. Chen et al. (2001) examined the economic damages in the agricultural sector arising from a shift in frequency and strength of ENSO events that might occur under climate change. The consequences involved changes in both the level and variability of agricultural outputs and prices. Event information and crop mix adaption on the part of farmers can partially offset the damages.

Chen and McCarl (2000) studied the forecast value on ENSO information considering phase event frequency and strength. They concluded that future studies should incorporate event strength in the analysis, and that US consumers and the rest of the world would receive welfare gains due to adaptations to ENSO phase information. Reilly et al. (2003) examined the effects of potential changes in ENSO on economic performance and yield variability. They found increases in ENSO intensity and frequency causes increases in economic losses. They also found that the resulting damages could not be completely offset even with farmer adaption with perfect forecasts of ENSO events. Chen et al. (2005) studied effects in the Texas Edwards Aquifer region and found regional benefits from conditioning water and agricultural management on ENSO phase forecasts. Kim and McCarl (2005) estimated the value of information on the North Atlantic Oscillation (NAO) for US agriculture. They found that the NAO impacts on crop yields are generally as large as the crop yield implications from ENSO phenomena particularly in the Midwest. Tack and Ubilava (2012) estimated the impacts that ENSO had on the mean and lower tail of the county-level corn yield distributions for Arkansas, Mississippi, and Texas. Their analyses also examined the second and the third moments. They found that the extreme ENSO events caused damages to crop yields with asymmetric impacts across non-neutral ENSO events and spatially heterogeneous impacts.

Mehta et al. (2012) found major DCV impacts on dryland corn and wheat yields in the Missouri Basin explaining as much as 40-50% of the variation in the average yield of corn and wheat in some locations: and also with effects on basin-wide aggregate crop yields. Generally, they found spring wheat yields increased (decreased) by 5–20% under the PDO+ (PDO−) and TAG− (TAG+) phases. They also found that anomalous precipitation and temperatures under the PDO+ and TAG− phases can generally result in below-average corn yields in the northwestern Missouri River Basin.

Analyses of Effects of Climate Change on US Crop Yields

A number of previous studies have considered the effect of climate change on crop yields (Adams et al. 1990; Semenov and Porter 1995; Easterling et al. 1996; Lobell and Burke 2010; Reilly et al. 2002; Rosenzweig et al. 2002; Tubiello et al. 2002; Chen, McCarl, and Schimmelpfennig 2004; Chen and Chang 2005; Schlenker et al. 2005; Lobell et al. 2006; Schlenker et al. 2006; Lobell and Christopher 2007; Schlenker et al. 2007; McCarl, Villavicencio, and Wu 2008; Tebaldi and Lobell 2008; Schlenker and Roberts 2009; Challinor et al. 2010; Welch et al. 2010; Attavanich 2011; Attavanich and McCarl 2011; Foley et al. 2011; Anwar et al. 2012; Park 2012). Collectively these show a potential negative impact of climate change on US agriculture. See comments and correspondence from Deschênes and Greenstone (2007), Deschênes and Greenstone (2012), and Fisher et al. (2012). McCarl, Villavicencio, and Wu (2008) incorporated interaction terms between temperature and US state regions and found that the effects of temperature on crop yields are heterogeneous across locations. They also found that projected precipitation changes have a negative impact on wheat. Chen, McCarl, and Schimmelpfennig (2004) found that precipitation enhances yields of corn, cotton, soybeans, winter wheat, and sorghum. McCarl, Villavicencio, and Wu (2008) found that projected climate change has a negative impact on yields of all crops. They also employed measures of wet days and drought severity and found that an increase in wet days decreases all crop yields, while an increase in a Palmer Drought Index (meaning less drought) increases yields of corn, soybeans, sorghum, and winter wheat, but decreases cotton yield.

Several studies have considered the influence of climate effects on yield variability (Chen, McCarl, and Schimmelpfennig 2004; McCarl, Villavicencio, and Wu 2008; Attavanich 2011; Attavanich and McCarl 2011; Park 2012). Chen, McCarl, and Schimmelpfennig (2004) found that high annual total precipitation increases the variability of sorghum and soybean yields, but McCarl, Villavicencio, and Wu (2008) found the opposite result. McCarl, Villavicencio, and Wu (2008) also found that there is no statistical significant evidence for a relationship between the drought index and crop yields. Chen, McCarl, and Schimmelpfennig (2004) concluded that high temperature reduces yield variation for cotton and sorghum, while it increases yield variation for corn, soybeans, and winter wheat.

Studies on Crop Yield Higher Order Moments

A few studies have taken into account higher moments of the yield distribution. The recent literature disagrees on whether crop yields should express nonzero skewness

(Hennessy 2009a). Empirical studies found negative crop yield skewness, but the literature provides few clear insights as to whether and why crop yields should express nonzero skewness (Hennessy 2009a). Hennessy (2009a, 2009b) revealed that statistical laws on aggregates do not imply a normal distribution. Atwood, Shaik, and Watts (2002) found statistical evidence against normality for farm-level data on various crops and US states, 1988–1997. Atwood, Shaik, and Watts (2003) identified non-normality for farm-level corn, sorghum, and wheat in Kansas. Both studies detected significant negative skewness. Ramirez et al. (2003) have discerned negative skewness for Iowa corn and soybeans using annual average data over 1950–1999, and positive skewness for Texas Plains dryland cotton, 1970–1999. Sherrick et al. (2004), with University of Illinois data 1992–1999, have found very suggestive evidence for negative skewness in corn and soybean yields.

Hennessy (2009b) concluded that although the approaches may have been flawed in certain ways, the studies generally suggest the existence of nonzero skewness. For the Corn Belt, he argued that for corn and soy-beans, evidence points strongly toward negative skewness. Tack et al. (2012) found for Arkansas, Mississippi, and Texas upland cotton that climate and irrigation affect the shape of the yield distribution. Their results show that the importance of the other conditioning variables is location-specific. The precipitation for dryland acreage appears to be important for conditioning all three moments in Texas, but not for Arkansas or Mississippi. The precipitation for irrigated acreage is important for all three moments in Mississippi, but is important for only the first moment in Arkansas. The technological change only appears to affect the first moment in Arkansas, but not in Mississippi or Texas. Park (2012) explored how climate change impacts the crop yield distribution. Using the flexible moment based approach, this study indicated that external climate factors influence not only mean crop yield, but also higher order moments. The climate effects on each moment vary by crops and location-specific. Many existing studies found that crop yields exhibit significant skewness (Swinton and King 1991; Goodwin et al. 1998; Wang et al. 1998; Just and Weninger 1999; Ramirez et al. 2003; Henessey 2009a, 2009b; and Du et al. 2012).

Econometric Model and Methodology

Since the previous studies have established that crop yield distributions generally do not follow normal distributions, we will use a less restrictive, general statistical distribution assumption in our analysis. To estimate the effects of DCV phenomena on crop yields, we use the skew-normal regression approach that yields estimates of the mean, variance and skewness (Henze 1986; Azzalini and Dalla Valle 1996; Azzalini and Capitanio 1999; Gupta and Chen 2001). Skew-normal regression assumes an underlying univariate skew normal distribution (Henze 1986; Azzalini and Dalla Valle 1996; Azzalini and Capitanio 1999; Gupta and Chen 2001). Denote the skew-normal distribution by $SN(y;\xi,\omega^2,\alpha)$, which has the following density form:

(1) $$f_{SN}(y;\xi,\omega^2,\alpha) = 2\omega^{-1}\phi(z)\Phi(\alpha z), \; y \in (-\infty,\infty)$$

where $z = \omega^{-1}(y-\xi)$, $\xi \in (-\infty,\infty)$ is a location parameter, $\omega > 0$ is a scale parameter, $\phi(.)$ and $\Phi(.)$ are the probability density function and cumulative density function of the standard normal distribution. The term $2\Phi(\alpha z)$ is a skewness factor controlled by a shape parameter $\alpha \in (-\infty, \infty)$. This distribution is skewed to the right when $\alpha > 0$; skewed to the left when $\alpha < 0$; and reduced to the normal distribution when $\alpha = 0$. Thus, we estimate mean, variance, and skewness parameters, where the latter describes the asymmetry of the distribution. See the explanation on decomposition of mean, variance, and skewness from centered parameterization in Appendix B.

We will estimate a linear regression assuming the error terms are skew normal,

(2) $$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \varepsilon$$

where $x_1, \ldots, x_p$ define covariates value, $\beta_0, \ldots, \beta_p$ are the unknown regression coefficients, and ε is the skew-normal error term $\varepsilon \overset{iid}{\sim} SN(0, \omega^2, \alpha)$. It follows that the yield distribution is also skew-normal. Because the mean μ of a skewed random variable is not the same as the location parameter ξ, then $E(\varepsilon) \neq 0$ (unless $\alpha = 0$) and this is unlike the standard normal linear regression model. In particular the mean error term is not zero and equals $E(\varepsilon) = \sqrt{2/\pi}\omega\delta$, where $\delta = \alpha / \sqrt{1+\alpha^2}$. It follows that $E(y) = \xi + E(\varepsilon)$.

One useful property of skew-normal distribution is that its normalized random variable does not depend on shape parameter (as shown by Genton et al. 2001). For instance, if $y \sim SN(\xi, \omega^2, \alpha)$, then $(y-\xi)^2 / \omega^2 \sim \chi_1^2$. This property provides an approach for evaluating model fit and statistical inference based on the standard chi-squared distribution.

Empirical Specification

Now we turn to an empirical investigation of the crop yield, output and revenue distributions as influenced by DCV phenomena. We follow approaches used in previous literature regarding climate effects and skewness. We use a panel data regression model and follow previous studies in selecting independent variables. We include weather variables giving temperature, precipitation, drought incidence, and their intensity plus a polynomial time trend as a proxy for technological progress as done in Chen et al. (2004), Schlenker et al. (2007), McCarl, Villavicencio, and Wu (2008), Schlenker and Roberts (2009), Attavanich (2011), Berry and Schlenker (2011), and Park (2012). We also include dummy variables for ENSO following Attavanich (2011), Tack and Ubilava (2012), and Tack and Ubilava (2013).

Data and DCV Phase Combinations

We estimate the DCV effects for yields, total production and revenue of the US major crops of corn, cotton, sorghum, soybeans, and wheat over panel data for 1950-2012 and for each of the 48 US contiguous states. To do this we assembled data on agricultural yields, crop acreage and prices, temperature, precipitation, drought, hot or wet days, ENSO phases, and joint decadal climate variability phase combinations of PDO, TAG, and WPWP. This section describes those data.

Data Sources

Agricultural Yields, Harvested Acres and Prices – We use state-level annual agricultural data on annual crop yields, harvested acreages, and prices farmers received for the 48 US contiguous states. The crops included are corn, cotton, sorghum, soybeans, and wheat. The data are for the years 1950-2012. The data come from the USDA National Agricultural Statistics Service website (USDA-NASS 2013). Not all states grow all crops, so the numbers of observations vary across crops. We calculate total crop production by multiplying yields times harvested acreage. We also calculate revenue multiplying total production times prices. The state-level nominal prices are prices received by farmers[3]and are adjusted to real 2012 dollars (=100). To do this we use the general consumer price index from US Bureau of Labor Statistics (BLS 2013).

Weather Data – The state-level annual temperature, precipitation, and drought data were drawn from the NOAA Global Summary of the Day database (NOAA-NCDC 2013a) and are annual average temperatures (in degrees Fahrenheit), total precipitation (in inches), and Palmer Drought Severity Index (PDSI). Weather intensity measures are derived from daily data with a temperature variable counting the number of days in a month with maximum temperature greater than or equal to 90° F and a precipitation variable giving the number of days in the month with greater than or equal to 1.0 inch of precipitation. These data were from the NOAA Custom Monthly Summaries of Global Historical Climatology Network database (NOAA-NCDC 2013b). When drawing out these data we used select NOAA weather stations that had complete coverage for the period 1950-2012. The list of all used weather stations is provided in the Appendix. We constructed state-level annual averages for temperatures and drought. We compute annual PDSI and weather intensity measures by state by averaging from monthly observations to a yearly level. We drop cases for crops in a state that have few

[3] Annual surveys from the USDA's National Agricultural Statistics Service (USDA-NASS 2013).

observations (less than 7). This resulted in dropping observations for 4, 1, and 2 states for corn, cotton, and sorghum, respectively.

Ocean Phenomena Data –For ENSO we use the NOAA Oceanic Niño Index (ONI) for identifying the phases of El Niño, Neutral, and La Niña (NOAA-NCEP 2013a). El Niño events are designated when the index is at or above the +0.5 for 5 consecutive months. La Niña events are designated when the index is at or below the -0.5 for 5 consecutive months in a year. The rest are called Neutral events. The annual DCV phenomena phase combinations are identified using monthly data for 1950-2012 as will be discussed next.

DCV Phase Combination Identification

Following Mehta et al. (2011, 2012), we use individual indices for each of the three DCV phenomena. The PDO index is that developed by Mantua et al. (1997) using data from NOAA-NCDC 2013c. The TAG and WPWP indices follow Reynolds et al. (2002). The indices were obtained from NOAA-ERSSTv3b. In turn we computed the annual average of each index and subtracted its mean value over 1950-2012 to get an anomaly index with positive and negative phase combinations. In turn and again following Mehta et al. (2011, 2012), we updated the DCV data and filtered their indices with a low-pass filter.

We placed each year into one of 8 categories reflecting the joint occurrence of all three DCV phenomena. Therefore, we define the set of DCV combinations as the ordered occurrence on negative (-) or positive (+) phase combinations of the PDO, TAG, and WPWP events. For example, the tuple (PDO-,TAG-,WPWP+) represents the DCV event with a negative PDO, a negative TAG plus a positive WPWP.

Model Specification

We estimate the regional direct and indirect effects of DCV phenomena on US crop yields. The indirect effects involve DCV effects on temperature, precipitation, drought, counts of hot days, and counts of high precipitation days which in turn have influence on yields, total production and revenues. The direct effects will involve direct estimation of the DCV phase combinations on yields, output, and production. Consequently, we use a two stage procedure where we first estimate the impacts of the various DCV phase combinations on temperature, precipitation, drought, and weather intensity using a quadratic specification with simple linear and squared effects. Then in the second stage we look at the effects of the climate parameters and the phase combinations directly on yields, output, and revenue.

The panel estimation accounts for the spatial-temporal heterogeneity in weather data and yields by incorporating time trends and location-specific dummy variables in a random effects model, which is called a mixed effects model (Pinheiro and Bates 2000) for the weather variables, in count models for the weather intensity variables, and in a skew-normal regression model for crop yields. We estimate mean, variance, and skewness effects for different DCV phase combinations by constructing a base case excluding all statistically significant regional DCV effects and comparing their statistical moments with another simulated DCV-specific average crop yields.

Table 1: Variables in regression analysis

Variables	Descriptions
Yield	Crop yields in bushels/acre, except cotton is in lbs/acre
Trend	Time trend where the data range from 1950 to 2013
$Trend^2$	Time trend in square
Harvested	Land area devoted to a particular crop in a given year in acres
Temperature	Average growing season temperature in degrees Fahrenheit
Precipitation	Annual total precipitation in inch
PDSI	Palmer Drought Severity Index
Day Temp>90°	Number of days with maximum temperature greater than or equal 90° F
Day Precip>01	Number of days with greater than or equal to 1.0 inch of precipitation
El Niño	Positive/negative annual phenomena of Warm ENSO event
La Niña	Positive/negative annual phenomena of Cool ENSO event
PDO	Positive/negative annual phenomena of Pacific Decadal Oscillation SST
TAG	Positive/negative annual phenomena of Tropical Atlantic SST Gradient Variability
WPWP	Positive/negative annual phenomena of West Pacific Warm Pool Average SST
C1	Dummy variable of (PDO+, TAG-, WPWP-)
C2	Dummy variable of (PDO-, TAG+, WPWP-)
C3	Dummy variable of (PDO-, TAG-, WPWP+)
C4	Dummy variable of (PDO+, TAG+, WPWP-)
C5	Dummy variable of (PDO+, TAG-, WPWP+)
C6	Dummy variable of (PDO-, TAG+, WPWP+)
C7	Dummy variable of (PDO+, TAG+, WPWP+)
R1	Dummy variable for Central region - IA, IL, IN, MI, MN, MO, OH, WI
R2	Dummy variable for Mountains region - AZ, CO, ID, MT, NM, NV, UT, WY
R3	Dummy variable for Northeast region - CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT
R4	Dummy variable for Northern Plains region - KS, ND, NE, SD
R5	Dummy variable for Pacific region - CA, OR, WA
R6	Dummy variable for Southeast region - AL, FL, GA, KY, NC, SC, TN, VA, WV
R7	Dummy variable for Southern Plains region - AR, LA, MS, OK, TX

Independent Variables Used

This study will investigate the impacts of climate, DCV and ENSO phenomena on yields. We choose the explanatory variables based on previous studies of regression analysis on crops such as Chen and Chang (2005), Attavanich (2011), Park (2012), Baker et al. (2013), etc. We use the regional dummy variables for 7 DCV phase combinations with (PDO-,TAG-,WPWP-) as the base case. We use the regional dummy variables for ENSO phases with neutral phase as the base case. We also have US state dummy variables. Table 1 lists the variables used.

DCV Effects on Weather

For the weather variables of temperature, precipitation, and Palmer Drought Index (which are continuous) we use:

(3a) $$w = g(X^{w}, \alpha^{w}) + u$$

where w is the temperature and its square, precipitation and its square, and PDSI and its square; $g(\cdot)$ is the parametric mean function; X^{w} is a vector of explanatory variables which are time and its square, dummy variables for ENSO phase as they interact with dummy variables for agricultural regions[4], interactions between dummy variables for the DCV phase combinations and dummy variables for agricultural regions, dummy variables for agricultural regions, and dummy variables for US contiguous states; α^{w} is

[4] These regions are Central (IA, IL, IN, MI, MN, MO, OH, WI); Mountains (AZ, CO, ID, MT, NM, NV, UT, WY); Northeast (CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); North Plains (KS, ND, NE, SD); Pacific (CA, OR, WA); Southeast (AL, FL, GA, KY, NC, SC, TN, VA, WV); and South Plains (AR, LA, MS, OK, TX).

the vector of estimated parameters; u is a normally distributed error term which is assumed to have a mean of zero. We then obtain estimates on how much the weather changes when the dummy variable for the DCV phase combinations switch, $\Delta g(\cdot)/\Delta DCV$, which we will use in the second phase of the estimation.

For the weather variables which are count data on number of hot days and highly precipitation days we estimate:

(3b) $$\log(w^*) = g^*(X^{w^*}, \alpha^{w^*}) + v$$

where w^* is the vector of count data weather variables which are average number of days in a month with maximum temperature greater than or equal 90° F and average number of days in a month with greater than or equal to 1 inch of precipitation[5]; $g^*(\cdot)$ is a parametric linear-response function in the framework of generalized linear model (GLM) by Nelder and Wedderburn (1972); X^{w^*} is a vector of explanatory variables which are the same as in the continuous weather variable model above; α^{w^*} is the vector of estimated parameters; v is assumed to be an asymptotically distributed normal disturbance term with mean of zero. In turn the estimation yields a measure of the influence of DCV phase combinations on the count data weather variables when the phase combination switches $\Delta g^*(\cdot)/\Delta DCV$. We will use this later after the crop yield equations.

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[5] We consider Poisson, negative binomial, and their zero-inflated versions for nonnegative integer-valued aspects of number of days. See Appendix for details on their marginal effects.

Estimating Yield Equations

Now we estimate the 'direct' DCV effects on crop yields. To do this we estimate a skew-normal regression that relates crop yields to DCV phenomena and other variables:

(4) $$y = f(X, \beta) + \varepsilon$$

where y is the crop yield; $f(\cdot)$ is the production function; X is a vector of all explanatory variables which are time trend and its square, temperature and its square, precipitation and its square, PDSI and its square, interactions between ENSO dummy variables and dummy variables for agricultural regions, interactions between dummy variables for DCV phase combinations and dummy variables for agricultural regions, dummy variables for agricultural regions, and dummy variables for US contiguous states; β is the vector of estimated parameters; ε is the skew-normal distributed disturbance term with zero mean, $\varepsilon \overset{iid}{\sim} SN(0, \omega^2, \alpha)$. After this estimation, we have $\Delta f(\cdot)/\Delta DCV$ as the regional 'direct' effects of DCV on crop yields.

Deriving Total Effects

Given the above equations (3a), (3b), and (4), we then use the estimated parameters to determine the total marginal effect of DCV phenomena on crop yields:

(5) $$\frac{\Delta y}{\Delta DCV} = \frac{\Delta f(\hat{y})}{\Delta DCV} + \sum_{\forall w} \left(\frac{\Delta f(\hat{y})}{\Delta w}\right)\left(\frac{\Delta g(\hat{w})}{\Delta DCV}\right) + \sum_{\forall w^*} \left(\frac{\Delta f(\hat{y})}{\Delta w^*}\right)\left(\frac{\Delta g^*(\hat{w}^*)}{\Delta DCV}\right)$$

The DCV impacts are evaluated at the regional level by associating them with regional dummy variables. In turn, we can evaluate the predicted mean of crop yields for each DCV phenomena. We can also investigate the DCV impacts on the crop distributions. To do this, we subtract all observations with the historical DCV events multiplied by all estimated coefficients for having the negative (zero event) phenomena impacted averaged yields for (PDO-,TAG-,WPWP-) as the base case. We estimated the impacted of the other seven DCV phase combinations by adding on average yields the significant regional DCV coefficients to the predicted yields for the base case.

We also follow the same approach as previously done (in Coble et al. 2000; Young and Westcott 2000; Nyambane et al. 2002; Sherrick et al. 2004; Bokusheva et al. 2006; and Benítez et al. 2006) to estimate and perform statistical inference for the consequences of DCV phase combinations on crop output and revenue distributions to evaluate the economic impacts of DCV phenomena. We estimate harvested land and crop price to account on for their dynamic adjustment to the DCV phenomena and, in addition, at different ENSO phases. Thus, the estimated output and value of crop produced will not be as influenced by changes in state-level agricultural prices due to farmer adaptation through land allocation.

Estimation Results and Discussion

Table 2 contains summary statistics of crop yield per acre, total production and revenue. The crop yield per acre is the yield per harvested acre. The total production and crop revenues give an indication of the regional crop importance. The crop outputs equal yield per harvested acre multiplied by acres harvested. The revenue is output by crop multiplied by the real crop price. The table reports the sample mean over years of outputs and revenues. We estimate crop outputs and revenues for different DCV phase combinations using log-skew-normal distribution.

Now we examine our basic findings for crops in DCV phase combinations. We find the phase combination (PDO-,TAG+,WPWP-), to be the one associated with the lowest average yields for all crops.

Similarly, the events with (PDO+,TAG-,WPWP+) and (PDO-,TAG+,WPWP+) phase combinations have the highest average yields. A similar pattern occurs with real revenue. The event (PDO-,TAG+,WPWP-), has the lowest revenue for all crops while (PDO-,TAG+,WPWP+) has the highest revenue for almost all crops, with the event (PDO-,TAG-,WPWP+) being the highest for sorghum revenue. In contrast, the event (PDO+,TAG-,WPWP+) provides lowest crop output for all crops. The events where the maximum output occurs vary but mostly are (PDO-,TAG-,WPWP+). The similar pattern of crop yields and revenues is no surprise due to commodity price inelasticity. For instance, the common phase combinations for lowest (highest) yield also have lowest (highest) revenue.

Table 2: US and regional level annual descriptive statistics (1950-2012)

	Yield Per Acre			Total Regional Output					Crop Revenues(million $)				
	N	Mean	S.D.	N	Total	%	Mean	S.D.	N	Total	%	Mean	S.D.
CORN													
United States	2,634	90.5	42.5	441	434,164	100.0%	984	1,763	441	1,692,241	100.0%	3,837	11,733
Central	504	101.5	35.7	63	297,343	68.5%	4,720	1,968	63	1,112,784	65.8%	17,663	25,328
Mountains	441	102.2	49.1	63	6,424	1.5%	102	71	63	29,859	1.8%	474	701
Northeast	366	84.5	28.8	63	12,433	2.9%	197	75	63	49,604	2.9%	787	1,051
Northern Plains	252	83.8	40.8	63	76,402	17.6%	1,213	797	63	340,350	20.1%	5,402	9,074
Pacific	189	129.5	49.5	63	2,412	0.6%	38	21	63	11,084	0.7%	176	229
Southeast	567	72.1	32.9	63	25,714	5.9%	408	90	63	81,981	4.8%	1,301	1,584
Southern Plains	315	78.8	43.8	63	13,436	3.1%	213	155	63	66,579	3.9%	1,057	1,796
COTTON													
United States	1,094	603	273.7	336	413,345	100.0%	1,230	1,413	256	27,171	100.0%	106	179
Central	87	530.8	229.8	63	12,303	3.0%	195	101	41	922	3.4%	22	28
Mountains	149	869.4	283.1	63	28,776	7.0%	457	136	63	1,818	6.7%	29	30
Northeast													
Northern Plains	31	419.6	174.8	31	440	0.1%	14	17	29	47	0.2%	2	2
Pacific	53	1117.2	240.1	53	54,399	13.2%	1,026	349	41	4,166	15.3%	102	62
Southeast	469	523.8	191.2	63	87,358	21.1%	1,387	812	41	6,039	22.2%	147	173
Southern Plains	305	544.6	217.5	63	230,070	55.7%	3,652	1,242	41	14,179	52.2%	346	289

Table 2: Continued

	Yield Per Acre			Total Regional Output					Crop Revenues(million $)				
	N	Mean	S.D.	N	Total	%	Mean	S.D.	N	Total	%	Mean	S.D.
SORGHUM													
United States	1,313	51.9	21.1	375	35,842	100.0%	96	124	375	84,688	100.0%	226	404
Central	186	66	19	63	2,323	6.5%	37	31	63	5,515	6.5%	88	83
Mountains	179	48.9	22.7	63	1,299	3.6%	21	11	63	2,527	3.0%	40	31
Northeast	11	64.5	17	11	3	0.0%	0	0	11	14	0.0%	1	1
Northern Plains	189	52.4	21.3	63	16,165	45.1%	257	111	63	40,602	47.9%	644	578
Pacific	49	72.6	13.7	49	497	1.4%	10	8	49	489	0.6%	10	8
Southeast	384	45.8	17.9	63	576	1.6%	9	11	63	1,347	1.6%	21	27
Southern Plains	315	49	20.1	63	14,978	41.8%	238	92	63	34,194	40.4%	543	470
SOYBEANS													
United States	1,885	27.5	8.7	315	108,015	100.0%	343	506	315	1,048,924	100.0%	3,330	7,886
Central	504	32.4	9.1	63	73,040	67.6%	1,159	612	63	698,561	66.6%	11,088	14,485
Mountains													
Northeast	298	27.9	8.2	63	1,715	1.6%	27	18	63	18,367	1.8%	292	448
Northern Plains	252	26.5	9.6	63	13,141	12.2%	209	213	63	165,035	15.7%	2,620	4,526
Pacific	520	25	7.1	63	9,137	8.5%	145	81	63	77,033	7.3%	1,223	1,473
Southeast													
Southern Plains	311	24.4	6.7	63	10,983	10.2%	174	80	63	89,928	8.6%	1,427	1,754

Table 2: Continued

	Yield Per Acre			Total Regional Output					Crop Revenues(million $)				
	N	Mean	S.D.	N	Total	%	Mean	S.D.	N	Total	%	Mean	S.D.
WHEAT													
United States	2,624	39.2	16.9	441	116,955	100.0%	265	230	441	512,524	100.0%	1,162	1,902
Central	504	42.3	13.7	63	19,069	16.3%	303	82	63	73,450	14.3%	1,166	1,220
Mountains	504	41.5	24.4	63	18,707	16.0%	297	89	63	87,645	17.1%	1,391	1,680
Northeast	315	42.8	12.8	63	1,833	1.6%	29	6	63	6,814	1.3%	108	131
Northern Plains	252	29.6	9.6	63	44,534	38.1%	707	206	63	197,210	38.5%	3,130	3,588
Pacific	189	51.3	18.5	63	12,398	10.6%	197	67	63	58,637	11.4%	931	1,039
Southeast	550	37	12.9	63	4,701	4.0%	75	45	63	22,790	4.4%	362	505
Southern Plains	310	31.5	11.6	63	15,714	13.4%	249	106	63	65,979	12.9%	1,047	1,143

Note: Yields of all crops are in bushels/acre, except for cotton yield which is in lbs/acre. Output is in thousands of bushels in a region, except for cotton is in thousands of lbs. All revenues are in million dollars for the region in real 2012 dollars. Yields were calculated from USDA data of US states and years. Outputs and revenues were calculated from summation over US states for a particular year and then sample averaged over years.

DCV Impacts on Climate

To do the estimation we follow standard panel data specification tests as discussed in Wooldridge (2002). In general, we have a complete balanced panel for the climate and ocean phenomena variables. Before estimating we run tests regarding model specification. First, we test and then chose to use a random effects model as opposed to a fixed effects specification based on Hausman's specification tests. Second, use of the Phillips-Perron tests with 12 Newey-West lags shows that there is no unit root problem in all models, thus indicating our model does not have the problem of spurious regression. Thus, we use a cluster-robust standard error estimator following Deschênes and Greenstone (2007, 2012) and Tack et al. (2012). That procedure provides consistent estimates of the asymptotic variance of the regression estimator given possible spatial correlation and heleroskedasticity. The count variable models for the frequency of hot days (Day Temp>90°) and the frequency of wet days (Day Precip>01) are also estimated in a random effects setting. The final models are selected from several alternative model specifications involving alternative independent variable configurations. For example, we considered several model options with a variety of regional and/or state dummy variables.

For the two count data regressions, we use the same set of explanatory variables. We select the best fitting model based on maximum log-likelihood and Akaike/Bayesian Information criteria comparing among a class of generalized linear models which are zero-inflated negative binomial model and zero-inflated Poisson panel data models. We fit the count variables with time trends, dummy variables for region, dummy variables for US states, dummy variables for ENSO, and regional dummy variables for occurrence of the 7 DCV phases. We follow the generalized linear model approach as in Furrer and Katz (2007). Our best model for the frequency of hot days (Day Temp>90°) is the zero-inflated Poisson regression model, and for the frequency of wet days (Day Precip>01) is the Poisson regression model. After estimation the explanatory performance is high for temperature and wet day variables as the Chi-square tests for goodness-of-fit provide satisfactory results. Both Poisson and zero-inflated Poisson models have the logit link function as the usual log-linear regression (Barry and Welsh 2002; Zuur et al. 2009; Hilbe 2011).

Marginal effects of the DCV variables are computed. The marginal effect from the logit link function of Poisson regression is the estimated coefficients divided by the sample average of the dependent variable. The marginal effects for the zero-inflated Poisson model are detailed in Appendix B.

We find that the DCV phase combinations have regionally varying, significant effects on temperature, precipitation, and drought incidence (Table 3). To check the validity of our results we compare our DCV effects with those from Mehta et al. (2011) for the Missouri River Basin region. They found strong DCV phenomena associations with regional temperature and precipitation. They found that during PDO+ that precipitation was above average almost everywhere and temperature was lower than average. In the TAG+ phase they found precipitation was below average almost everywhere and temperature was increased almost everywhere. In terms of WPWP impacts they found the effects varied geographically and generally had less impact than PDO and TAG. To compare the results we examine the regions that overlap with the MRB which are R1: Central (IA, IL, IN, MI, MN, MO, OH, WI), R2: Mountains (AZ, CO, ID, MT, NM, NV, UT, WY), and R4: Northern Plains (KS, ND, NE, SD). We consider (PDO+,TAG-,WPWP-) and (PDO-,TAG+,WPWP-). We have essentially the same results as in Mehta et al. (2011) with almost of our statistically significant terms having the same sign of effects. For example, for Northern Plains the (PDO+,TAG-,WPWP-) phase combination reduces temperature and the frequency of hot days (Day Temp>90°) but increases precipitation, mitigates drought, and increases the frequency of wet days (Day Precip>01). But the (PDO-,TAG+,WPWP-) has different directional impacts on temperature and negligible small effects on hot days. Collectively, the results in Central, Mountains, and Northern Plains are similar to Mehta et al. (2011)'s for the statistically significant coefficients.

We find that in several cases the DCV phase combinations tend to have differing regional effects including changes in sign, e.g. positive (negative) on north and negative (positive) on south, or similarly positive (negative) in east and negative (positive) in west.

Temperature

We find that the (PDO+,TAG-,WPWP-) phase combination increases temperature in the Central region but decreases it in the Northern Plains and Southern Plains. The (PDO-,TAG-,WPWP+) phase combination increases temperature in the Mountains and Northeast regions but decreases it in the Southeast and Southern Plains. The (PDO+,TAG-,WPWP+) phase combination increases temperature in the Pacific region but decreases in Central, Northeast, Northern Plains, Southeast, and Southern Plains. The (PDO+,TAG+,WPWP-) phase combination increases temperature in the Mountains and Pacific regions but decreases in the Central, Northeast, Northern Plains, Southeast, and Southern Plains. The (PDO-,TAG+,WPWP+) phase combination increases temperature in the Mountains region but decreases it in the Northern Plains, Southeast, and Southern Plains. The (PDO+,TAG+,WPWP+) phase combination increases temperature in Mountains, Northeast, and Pacific regions but decreases in Southeast and Southern Plains. The (PDO-,TAG+,WPWP-) phase combination only decreases temperature in Northern Plains and Southeast. The temperature squared mostly has the same direction of the effects from the simple linear climate variables.

Additionally we find that El Niño increases temperature in the Central and Southern Plains regions while it reduces temperature in Northeast. La Niña increases temperature in the Central, Northeast, Southeast, and Southern Plains but decreases it in the Mountains and Pacific.

Precipitation

We find the (PDO+,TAG-,WPWP-) phase combination increases precipitation in the Central and Northern Plains but decreases it in the Northeast and Southeast. The (PDO+,TAG-,WPWP+) phase combination increases precipitation in Mountains but decreases in Northeast. The (PDO+,TAG+,WPWP-) phase combination increases precipitation in Northeast, Northern Plains, Pacific, and Southeast, but decreases in Southern Plains. The (PDO+,TAG+,WPWP+) phase combination increases precipitation in the Mountains and Pacific but decreases it in the Southeast. The (PDO-

,TAG+,WPWP-) phase combination only decreases precipitation in the Central, Northeast, Southeast, and Southern Plains; the (PDO-,TAG-,WPWP+) phase combination decreases precipitation in the Mountains, Pacific, and Southeast; and the (PDO-,TAG+,WPWP+) phase combination decreases precipitation in Southeast and Southern Plains. The El Niño increases rainfall in the Northern Plains, Pacific, and South Plains, but La Niña reduces rainfall in the Northeast and Pacific.

Drought (PDSI)

The phase combination effects for drought exhibit a similar pattern as the impacts on temperature. The (PDO+,TAG-,WPWP-) phase combination increases drought in the Northern Plains but decreases in the Northeast, Pacific, and Southeast. The (PDO-,TAG-,WPWP+) phase combination increases drought in the Northern Plains but decreases in Mountains, Pacific, and Southeast. The (PDO+,TAG-,WPWP+) phase combination only increases drought in the Northern Plains, similar to the (PDO+,TAG+,WPWP-) phase combination which only increases drought in Northeast and Southeast. The (PDO-,TAG+,WPWP+) phase combination increases drought in Northeast and Northern Plains but decreases in Pacific and Southeast. The (PDO+,TAG+,WPWP+) phase combination increases drought in Central and Northern Plains but decreases in Southeast. The (PDO-,TAG+,WPWP-) phase combination only decreases drought in Central, Northeast, Southeast, and Southern Plains.

Additionally, an El Niño event enhances drought in the Pacific, while a La Niña event enhances it in the Mountains and Pacific. On the other hand, El Niño reduces drought in the Central, while La Niña reduces it in the Central and Southern Plains.

Hot Days (Log of Temperature Intensity)

The (PDO+,TAG-,WPWP-) phase combination increases hot days in the Southeast but decreases it in Northern Plains. The (PDO-,TAG-,WPWP+) phase combination increases hot days in Mountains, Northeast, and Southeast but decreases it in Southern Plains. The (PDO+,TAG-,WPWP+) phase combination increases hot days in the Southeast but decreases it in the Central and Northern Plains. The (PDO+,TAG+,WPWP-) phase combination increases hot days in Mountains and Pacific but decreases in Central, Northeast, Southeast, and Southern Plains. The (PDO-,TAG+,WPWP+) phase combination only increases hot days in the Mountains and Southeast; and the (PDO+,TAG+,WPWP+) phase combination only increases hot days in the Mountains, Northeast, Southeast, and Southern Plains. The (PDO-,TAG+,WPWP) phase combination only decreases hot days in the Northern Plains.

The El Niño increases hot days in Northeast, while La Niña decreases it in Central, Northeast, and Southeast. On the other hand, the El Niño only decreases hot days in the Mountains.

Wet Days (Log of Precipitation Intensity)

We find that the effects from climate variables on wet days are mostly the same direction with the effects on precipitation. The (PDO+,TAG-,WPWP-) phase combination increases wet days in Northern Plains but decreases in Northeast, Pacific, and Southeast. Similarly, the (PDO+,TAG-,WPWP+) phase combination increases wet days in Northern Plains but decreases in Northeast and Southeast. The (PDO+,TAG+,WPWP-) phase combination increases wet days in Northeast and Pacific but decreases in Southern Plains. The (PDO+,TAG+,WPWP+) phase combination increases wet days in Northern Plains and Pacific but decreases in Southeast. The (PDO-,TAG+,WPWP-) phase combination only decreases wet days in Central, Mountains, Southeast, and Southern Plains; the (PDO-,TAG-,WPWP+) phase combination decreases wet days in Pacific and Southeast; and the (PDO-,TAG+,WPWP+) phase combination decreases wet days in Southeast and Southern Plains.

The El Niño increases wet days in Northern Plains, while La Niña increases in Northern Plains and Pacific. We find no reduction effects on wet days from ENSO phenomena on other regions.

Weather and Climate Impacts on Crop Yields by Region

We now focus on how the non-DCV variables impact crop yields holding the DCV discussion for the next section. Note here we do not have a balanced panel as not all states grow all crops.

As discussed earlier, DCV phase combinations have effects on weather variables such as temperature, precipitation, drought, and extreme events and in turn this alters crop yields and productivity. We use the skew-normal regression to estimate crop yields using the explanatory variables as explained above. The results of Phillips-Perron tests with 12 Newey-West lags for each crop panel show that there is no unit root process for all crops. We evaluate skew-normal regression goodness-of-fit using the $\chi 2$ statistic from a Wald test. The $\chi2$ normal test based on likelihood-ratio statistics confirms that the regression disturbances are not (symmetric or) normally distributed.[6]

Results on Non-DCV Items

The major results for the non DCV items the skew-normal regression model are shown in Table 4. We do not report the coefficients for state and region dummy variables to save space. We find strong evidence on skewness, and this demonstrates asymmetry in the distributions of crop yields. Thus, estimating the crop yields based on the standard normal distribution could lead to biased inference.

In the regressions positive (negative) signs indicate a yield enhancing (reducing) effect of the independent variables on crop yield. Here we find that the more that is planted the lower is the yield likely showing more planting involves more marginal conditions. Also we find time, which is a proxy for technological progress has a positive linear effect and a negative quadratic effect for cotton, sorghum, and soybeans that is we see increasing yields over time but at a decreasing rate. The results are consistent with the finding of upward but diminishing trends in US crop yields as found in McCarl, Villavicenio, and Wu (2008), Feng (2012), Baker et al. (2013), and McCarl, et al. (2013).

The results show climate impacts on average yields. In particular, precipitation exhibits a significant positive linear term and a significant negative quadratic term. This suggests that holding all other involved variables constant, initially a higher level of total

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[6] Our normality tests on disturbances estimated from standard linear method also show that they are not normally distributed with strong evidence of asymmetry in the disturbance distribution for each crop.

precipitation increases corn, soybeans, and wheat yields but at a decreasing rate as precipitation increases and then it plateaus as found in Schlenker and Roberts (2009) and Attavanich (2011). For cotton and sorghum no significant precipitation effects are found perhaps reflecting that these crops are more drought tolerant ones.

We find higher temperature has a significant linear effect increasing yields for cotton and soybeans. We find a negative term for temperature squared implying a plateau then a decrease in yields as temperature rises as also found in Schlenker and Roberts (2009) and Attavanich (2011).

The PDSI which is positive when conditions are wetter has a significantly positive regressor for corn and soybeans, which implies yield decreases when droughts occur (as the index becomes negative). The squared drought term shows significant decreases in average yields of corn and soybeans as PDSI becomes larger in absolute value indicating moves toward extreme wet or dry conditions decrease yields.

For the effect of extreme high temperature, the frequency of hot days with maximum temperature higher than 90 °F implies a decrease in the yield of all crops. The count of wet days has no effects on crop yields except a small positive influence on sorghum.

In conclusion for direct effects on crop mean, we find negative impacts of extreme drought events and the quadratic terms of temperature, precipitation, and drought. The results confirm previous findings from McCarl, Villavicencio, and Wu (2008), Schlenker and Roberts (2009), and Attavanich (2011).

Results on DCV Impacts for Crop Yields

We combine the direct and indirect DCV effects into the total effects by region using the method discussed earlier. The results are reported in Table 5 and Table 6 for total DCV impacts and direct and indirect DCV impacts, respectively. We find some gains from DCV phase combinations on crop productivity, and a number of adverse impacts of DCV phase combinations on regional predicted mean crop yields (see Table 7). Figure 2 to Figure 6 maps the statistically significant effects illustrating the impacts by region. For corn, the crop yields in the Central region (which contributes 66% of corn revenue) decreases on average by 7% under the (PDO+,TAG-,WPWP+) phase combination and by 6% under (PDO+,TAG+,WPWP+) phase combination. Figure 2 also shows that the (PDO+,TAG-,WPWP+) phase combination adversely impacts corn yields in the western United States, while the (PDO+,TAG+,WPWP+) combination decreases corn productivity in a large area of the eastern United States. In contrast, the (PDO+,TAG-,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO-,TAG+,WPWP+), (PDO+,TAG+,WPWP+), and (PDO-,TAG-,WPWP-) phase combinations increase corn yield in the most part of western United States.

For cotton, Southern Plains (the major growing region with 52.2% of revenue) is significantly affected under the (PDO+,TAG+,WPWP+) combination as it reduces the cotton yield by 7%. The Figure 3 reveals that all the DCV phenomena but (PDO-,TAG+,WPWP+) diminishes crop yields on the Pacific region. All three pure DCV phenomena, (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), and (PDO-,TAG-

,WPWP+) have negative impacts on the South East areas as shown in Figure 3. The (PDO+,TAG+,WPWP+) phase combination also severely effects cotton productivity in a large areas of Central, Northern Plains, Pacific, Southeast, and Southern Plains. The phenomena of (PDO+,TAG-,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG+,WPWP), and (PDO-,TAG+,WPWP+) phase combinations enhance cotton productivity in the large central areas of United States especially in Central, Mountains, and Northern Plains.

For sorghum, the impacts are smaller with DCV phase combination impacts ranging between -1.5% to -3%. The DCV phase combinations that reduce Northern and Southern Plains yields are (PDO-,TAG-,WPWP+) and (PDO-,TAG+,WPWP+). We can see in the Figure 4 that in the more minor Mountain and North East regions yields suffer under (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations. However, the (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations increase sorghum yield in Southeast; while the (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO+,TAG+,WPWP-), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations increase in Southern Plains. The (PDO+,TAG-,WPWP-) phase combination induces an increase in sorghum productivity.

For soybeans, (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) phase combinations reduce the yields in the Central (66.6% of soybeans revenue) region by 5% and 9%, respectively. Furthermore, in the Northern Plains (15.7% of revenue) yields are decreased by 8% under the (PDO-,TAG+,WPWP-) phase combination, and in the Southern Plains (9% of revenue) by 15-18% under the (PDO-,TAG-,WPWP+) and (PDO+,TAG+,WPWP+) combinations. All pure DCV phase combinations which are (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+) have negative impacts on Pacific and North East regions. The yields are also reduced in the Pacific and Southern Plains which suffered under several DCV phase combinations. Central and Northern Plains as the major soybeans production regions are most impacted by (PDO-,TAG+,WPWP-) and (PDO+,TAG+,WPWP-) combination as shown in Figure 5. The (PDO-,TAG-,WPWP+) and (PDO+,TAG-,WPWP+) phase combinations increase its yield in Pacific. The (PDO+,TAG-,WPWP-), (PDO-,TAG-,WPWP+), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations enhance productivity of soybeans in Northern Plains and/or Central. The (PDO+,TAG-,WPWP+) phase combination increase yields in Southern Plains.

For wheat the Northern Plains (38.5% of wheat revenue) has 11%-15% reduction in wheat yields under the (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) combinations. Yields are also reduced in the Pacific (11% of wheat revenue) under the (PDO-,TAG+,WPWP-) combination by 11%. Figure 6 shows that Northern Plains' yields dropped under several DCV phase combinations. The (PDO+,TAG-,WPWP-), (PDO-,TAG-,WPWP+), and (PDO+,TAG+,WPWP+) increase yield in Pacific. The (PDO-,TAG-,WPWP+) phase combination increases yield in Mountain. The (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO+,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO-

,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations enhance yield in Southern Plains. The (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO-,TAG+,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations increase yield in Southeast. The (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), and (PDO+,TAG+,WPWP+) phase combinations increase in Northeast.

In conclusion for this section, the DCV effects on mean crop yields vary by region. We identify the total effects by combining direct effects (on crop yield) and indirect effects (through weather variables). The largest yield reductions occur in the major crop growing regions such as Central for corn; Southern Plains for cotton; Northern and Southern Plains for sorghum; Central, Northern Plains, and Southern Plains for soybeans; and Northern Plains and Pacific for wheat.

For the DCV direct effects on the higher order distribution moments, we evaluate the effects by regress the computed residuals obtained from the above regression. We use the squared, tripled, and quadrupled transformation of the predicted residuals as the estimates of the second, third, and fourth moments as in Park (2012).

Generalized-least Square Regression Results on Variance by Region

The regression results for the yield variance are presented in Table 8. The interpretation of a positive (negative) coefficient implies an increase (a decrease) in crop yield variance.

Results on Non-DCV Items

A higher temperature decreases yield variability in soybeans but increases yield variability in wheat. Wheat has lower variability over time. An increase in PDSI reduces corn variability, thus fewer droughts as measured by PDSI would decrease yield variability in corn. As Table 8 indicates, the joint significant test for cotton fails to reject the null hypothesis that the variability of cotton yields is not determined by explanatory variables in the model. However, the variability of corn, sorghum, soybeans, and wheat are jointly determined by the explanatory variables.

Consider Table 9, the incidence of La Niña is shown to reduce variability of sorghum yields in the Northeast. We find asymmetry in ENSO effects on cotton production variability in Southeast region such that both El Niño and La Niña increase variation in cotton yields in this region.

Other weather variables have no significant impact on the variance of crop yield distributions. The variance of corn, cotton, sorghum, and soybeans are not significantly related with the time trend. We could observe that, in general, the indirect DCV effects are smaller than the direct effects as reported in Table 10.

Results on DCV Impacts

In terms of DCV phenomena, we find for corn that (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) reduce variability in the Central region. The (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO-,TAG+,WPWP+), or (PDO+,TAG+,WPWP+) decrease yield variability in corn for the Mountains. The (PDO-,TAG-,WPWP+) phase combination increase corn yield variation in Northeast, and the (PDO-,TAG+,WPWP+) also increases corn yield variation in Southeast.

The (PDO+,TAG+,WPWP+) reduce variability in the Southeast region for cotton. For sorghum, the (PDO-,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO+,TAG+,WPWP+) decrease yield variability in sorghum for the Central region. The (PDO-,TAG-,WPWP+) phase combination increases sorghum yield variability for the Northeast. The (PDO+,TAG-,WPWP-) phase combination increases sorghum yield variability for the Northern Plains.

For soybeans, the (PDO-,TAG+,WPWP+) decreases soybeans yield variability in the Central region. For wheat, the (PDO+,TAG+,WPWP-) phase combination increases yield variability in the Central region, and the (PDO-,TAG+,WPWP+) phase combination decreases yield variability in the Central region. The (PDO-,TAG+,WPWP) phase combination increases variation in wheat yield for the Mountains region. The (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) phase combinations decrease wheat yield variability in the Southeast region, and the (PDO-,TAG+,WPWP-) phase combination reduces its variability in the Southern Plains region.

Generalized-least Square Regression Results on Skewness by Region

Now we address effects on regional crop yield skewness. In this case a positive coefficient implies that an increase in the associated variable leads the yield distribution to be more positively skewed, so negative results show a negative skew. A positive skew indicates the right tail is longer, the mass of the distribution is concentrated on the left of the curve, and it has relatively more values below the mean. On the other hand, a negative skew indicates the left tail is longer, the mass of the distribution is concentrated on the right of the curve, and it has relatively more high values.

As Table 11 indicates, the joint significant test for cotton fails to reject the null hypothesis that the skewness of cotton yields is not determined by the explanatory variables in the model. That is, the skewness of the yield distribution for cotton is symmetric and unaffected by external factors. However, the skewness of the yield distributions for corn, sorghum, soybeans, and wheat are jointly determined by the explanatory variables in the model.

Results on Non-DCV Items

Consider Table 12, skewness is relatively higher as time progresses for wheat which indicates non-stationarity in its third moment. Skewness increases with higher temperature at a decreasing rate for soybeans but decreases at an increasing rate for wheat. Higher PDSI increases skewness in corn yield as an increasing rate. Wet days decrease skewness of soybean yields. Both El Niño and La Niña increase skewness in the corn yield distribution for the Central region. The La Niña phenomenon decreases sorghum yield skewness for the Northeast region.

Results on DCV Impacts

Again, the indirect DCV effects on skewness are smaller as shown in Table 13. For corn, the DCV phenomena (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO-,TAG+,WPWP+), or (PDO+,TAG+,WPWP+) phase combinations increase skewness in the Mountains region. The (PDO-,TAG-,WPWP+) phase combination reduces skewness in the Northeast region, while the (PDO-,TAG+,WPWP+) phase combination reduces it in the Southeast.

For sorghum, the (PDO-,TAG-,WPWP+) phase combination decreases skewness in the Central, and the (PDO-,TAG-,WPWP+) phase combination increases skewness in the Northeast. For soybeans, the (PDO-,TAG+,WPWP+) phase combination increases skewness in the Central. The (PDO+,TAG-,WPWP-) phase combination reduces soybeans yield skewness in the Northern Plains region, while the (PDO-,TAG+,WPWP+) phase combination reduces its skewness in the Southern Plains. For wheat, the (PDO-,TAG+,WPWP-) phase combination increases skewness in the Central region, but the (PDO+,TAG+,WPWP-) phase combination reduces in the Central. Both the (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) phase combinations reduce the wheat yield skewness for the Mountains region. The (PDO+,TAG-,WPWP-) phase combination reduces wheat skewness in the Pacific region, while the (PDO-,TAG+,WPWP-) phase combination increases skewness in the Southeast, and the (PDO-,TAG+,WPWP-) phase combination increases skewness in the Southern Plains.

<u>Generalized-least Square Regression Results on Kurtosis by Region</u>

Now we examine the results on kurtosis as reported in Table 14. A positive coefficient therein implies the increase in the corresponding variable leads to an increase in the kurtosis of the yield distribution. A lower kurtosis means a flatter distribution with fatter tails, while a higher kurtosis implies a more peaked distribution with skinnier tails. The higher probability under the two-sided areas of tails implies higher chance of vulnerability. An increase in temperature increases kurtosis in soybeans but decreases kurtosis in wheat. Both of them have diminishing effects. We do not have the evidence of other effects on kurtosis from the weather variables. The kurtosis of wheat is negatively correlated with time trend.

Table 15 reports DCV and ENSO total effects. The indirect DCV effects on crop kurtosis are much smaller than direct effects as shown in Table 16. For the DCV effects on corn, We find that the occurrence of DCV such as (PDO+,TAG-,WPWP-), (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), (PDO+,TAG-,WPWP+), (PDO+,TAG+,WPWP-), (PDO-,TAG+,WPWP+), or (PDO+,TAG+,WPWP+) phase combinations would reduce kurtosis in Mountains region. The (PDO-,TAG-,WPWP+) phase combination increases kurtosis in the Northeast region, while the (PDO-,TAG+,WPWP+) phase combination increases kurtosis in the Southeast.

For cotton, the DCV phenomena have no effects on kurtosis of its yield distribution. We find that the (PDO-,TAG-,WPWP+), (PDO-,TAG+,WPWP+), or (PDO+,TAG+,WPWP+) reduce kurtosis in the sorghum distribution for the Central region. The (PDO-,TAG-,WPWP+) phase combination also increases kurtosis in sorghum distribution for the Northeast region.

For soybeans, the (PDO-,TAG+,WPWP+) phase combination decreases kurtosis of yield distribution in the Central. The (PDO+,TAG-,WPWP-) phase combination increases soybeans distribution's kurtosis in the Northern Plains, while (PDO-,TAG+,WPWP+) phase combination increases soybeans distribution's kurtosis in the Southern Plains.

For wheat, the (PDO-,TAG+,WPWP-) phase combination reduces kurtosis in the yield distribution for the Central, but the (PDO+,TAG+,WPWP-) phase combination increases its kurtosis in the Central. Both (PDO-,TAG+,WPWP-) or (PDO+,TAG-,WPWP+) phase combinations increase kurtosis for the Mountains. The (PDO+,TAG-,WPWP-) phase combination decreases kurtosis of wheat distribution in the Pacific. The (PDO-,TAG+,WPWP-) phase combination reduces kurtosis of wheat distribution in the Southeast, while the (PDO-,TAG+,WPWP-) phase combination reduces kurtosis of wheat distribution in the Southern Plains.

The La Niña events reduce the kurtosis of corn in the Central region. The El Niño increases cotton distribution kurtosis in the Southeast. For sorghum, the evidence of El Niño or La Niña would reduce the distribution kurtosis in the Northeast region. The El Niño increases kurtosis of wheat distribution in the Mountains region.

DCV Impacts on National Crop Yield Distributions

Now we report national level results regarding the crop yield mean, variance, and skewness estimated from the DCV phase combination regressions. The results are reported in Table 17.

We find the significant chi-square test results for the distribution moments of US yields, but insignificant tests for the joint equality of all moments at each DCV scenario compared with of the (PDO-,TAG-,WPWP-) case. At the national level, the DCV combination phases do not have significant impacts on mean yields or other higher order moments, but only increases in skewness of soybeans in some DCV phases. The increase in skewness of yield distribution indicates the longer right tail and the more concentration of the mass of the distribution on the left of the probability distribution curve. It implies the higher chance of fewer yields. When combining the adjustment on

DCV phenomena on weather variables and evaluating at t=2012, we find almost no difference in crop yield distributions for different DCV phase combinations. Figure 7 shows an example of DCV impacts on national yield distribution of corn. Other crops have similar findings that DCV have no significant impacts at the national level.

Evaluating DCV Impacts in Interaction with ENSO Scenarios

After we control for time dependency, farmer adaptation on land harvested, and market adjustment via price mechanism; we find as shown in Table 18-25 and Figures 8-22 that DCV effects on crop yield, output, and revenue could be vary by ENSO phase. The estimated distribution moments (mean, standard deviation, and skewness) for national crop distributions are significantly different from zero based on Wald's statistics. However, the equality tests for DCV effects evaluated at different scenarios show that the estimated moments are not statistically different from the base case (PDO-,TAG-,WPWP-) at the national level. Accordingly, the changes for each crop at different DCV phenomena are very small in percentage. This is different from the results of the analysis without controlling for time, no farm adaptation, and no price adjustment in which DCV phenomena significantly alter national distributions' moments. Nevertheless, the revenue differences could be large in some of our controlled climatic scenarios with time independence of yield, output, and value of crop produced.

The DCV effects as measured with percentage change are small, but the ENSO effects are larger. Mostly the El Niño and La Niña phase combinations uniformly alter the average mean of yield, output, and revenue from the neutral phase. There are some specific cases that the ENSO causes heterogeneous patterns of DCV effects at some

DCV combinations especially the total DCV and ENSO effects on output and value of crops produced. The difference in crop revenue could gain or loss can be large in US dollars at the national level.

Yield

As discussed previously, we simulate yield for different DCV and ENSO scenarios, given their impacts at regional level. We control for time independency by evaluated at year 2012.

For corn, the DCV phenomena have small positive effects for crop yield especially for the three pure DCV phase combinations which are (PDO+,TAG-,WPWP), (PDO-,TAG+,WPWP-), and (PDO-,TAG-,WPWP+). But the sizes are smaller than the effects from ENSO. La Niña uniformly increases corn yield. On the other hands, El Niño uniformly decreases its yield at the similar effect sizes.

For cotton, (PDO-,TAG+,WPWP-), (PDO-,TAG-,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations decrease yield. Similar to corn, the DCV effects are smaller than the ENSO effects. The La Niña increases yield, but El Niño reduces it.

For sorghum, the DCV effects are also small in which (PDO-,TAG-,WPWP+) and (PDO+,TAG-,WPWP+) decrease sorghum yield from the base case level, but (PDO+,TAG-,WPWP-) and (PDO-,TAG+,WPWP+) increase yield from yield at (PDO-,TAG-,WPWP-) level. La Niña decreases sorghum yield more than under El Niño.

For soybeans, (PDO-,TAG+,WPWP-) tend to reduce yield from the base case level at the larger scale of effects than other DCV phase combinations. Similar to what happens for sorghum, both anomaly ENSO phase decrease soybeans yield, but El Niño decreases soybeans yield more than under La Niña.

For wheat, (PDO+,TAG-,WPWP-) and (PDO-,TAG+,WPWP+) increase crop yield, but (PDO-,TAG-,WPWP+) and (PDO+,TAG+,WPWP-) decrease its yield with smaller magnitude. The decrease from La Niña is larger than from El Niño. This effect is different from that found for corn and cotton in that only El Niño decrease crop yield, and from sorghum and soybeans that El Niño reduce yield than La Niña.

Output

We estimate output from predicted yield in previous section and the estimated acres harvested, which we controlled time at 2012 and also with regional DCV and ENSO effects to reflect farmer adaptation on crop investment. This assumes farmers adjust the decision in responding to weather and climate forecasts.

For corn, (PDO-,TAG+,WPWP-) reduces corn output but at a small level in percentage. Both El Niño and La Niña uniformly reduce the output level for all DCV phase combinations. The patterns of DCV effects are mostly very similar across ENSO events.

For cotton, (PDO-,TAG+,WPWP-) dominantly increase output level from the base case (PDO-,TAG-,WPWP-). On the other hand, (PDO-,TAG-,WPWP+) and (PDO+,TAG+,WPWP+) reduce output levels. La Niña uniformly reduces the output level. Both El Niño and La Niña limit the positive effect from (PDO-,TAG+,WPWP-) compared with the neutral phase.

For sorghum, the pattern of DCV effects on crop output is heterogeneous with specific patterns for the ENSO phases. Output is highest in (PDO+,TAG-,WPWP+) for neutral and El Niño. But (PDO+,TAG+,WPWP+) has the highest output level in La Niña phase. Under La Niña, all DCV phenomena reduce the output levels except (PDO+,TAG+,WPWP+).

For soybeans, the patterns of DCV effects are preserved across the ENSO phases. Only (PDO-,TAG+,WPWP-) significantly reduce output level. El Niño uniformly lessens the soybeans output level from the base case (PDO-,TAG-,WPWP-). But La Niña has no contribution on the effects to soybeans output.

For wheat, (PDO-,TAG+,WPWP-) increase crop output for all ENSO phases. The DCV effect patterns are similar for neutral and La Niña. Only in La Niña, we find that (PDO+,TAG-,WPWP-) reduces output while (PDO-,TAG+,WPWP+) increases wheat output from the base case (PDO-,TAG-,WPWP-).

Revenue

We estimate revenue from output in previous section and simulated price. Again, we control the estimated price for time independency and for regional DCV and ENSO impacts.

For corn, (PDO-,TAG+,WPWP-) could increase the value of corn produced up to $20 million. In contrast, the DCV phase combinations (PDO+,TAG-,WPWP-) and (PDO-,TAG-,WPWP+) reduce corn revenue but rather small. The ENSO phenomena uniformly reduce revenue from the neutral phase with effects from La Niña and El Niño at 25 and 30 million dollars, respectively. The positive effect from DCV phase combination (PDO-,TAG+,WPWP-) cannot compensate the adverse ENSO effects.

For cotton, the DCV effects are very small. However, the ENSO effects could worsen the cotton farmers' revenues uniformly at all DCV's anomaly events. The effects for ENSO phases are also small being about a million dollars for the whole country.

For sorghum, the effects from DCV vary by ENSO phase. The largest DCV effect is a negative one under (PDO-,TAG-,WPWP+), where the national revenue reduction is about $15 million in neutral and La Niña phase combinations. The clear heterogeneous pattern could be seen under La Niña in which (PDO-,TAG-,WPWP+) increases and (PDO-,TAG+,WPWP+) decreases crop revenue with a smaller effects when neutral and El Niño occur. On the other hand, only (PDO-,TAG+,WPWP+) increases revenue for $10 million under La Niña. Thus, the effects from DCV on sorghum revenue are heterogeneous across ENSO phases.

For soybeans, (PDO-,TAG+,WPWP-) increases crop revenue significantly. The effect size is rather small at around $5 million. The rest of DCV effects are much smaller. The El Niño phase reduces revenue for around $5 million while the La Niña phase reduces it by around $8 million.

For wheat, (PDO-,TAG+,WPWP-) significantly increases the value of wheat produced at around $15-25 million dependent on the ENSO phase. The negative effects from (PDO+,TAG-,WPWP-), (PDO-,TAG-,WPWP+) and (PDO+,TAG+,WPWP+) are large. Particularly, the (PDO+,TAG-,WPWP-) could reduce the crop revenue for around $8 million under La Niña. However, the (PDO,TAG-,WPWP+) phase combination reduces revenue by about $5 million under La Niña. The El Niño phase uniformly shifts revenue upward from the neutral phase. The impact size could be up to $5 million. But it is compensated with the negative DCV effects which were uniformly reduced under La Niña. The sizes of compensated effects from La Niña are similar to the negative effects from El Niño.

<u>Adaptation Possibilities from DCV Phase Combinations</u>

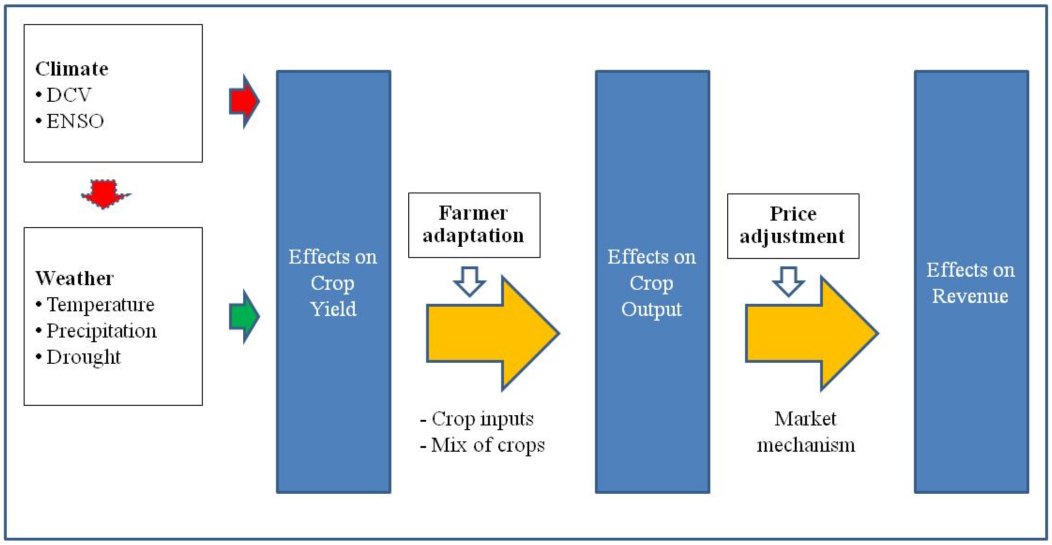
DCV forecasts could inform crop choice decision making by providing priori information on crop yields and other weather phenomena. This provides the opportunities to adapt agricultural production to responding to the changes in yields, temperature, precipitation and water supply, and increased frequency of extreme weather events in different DCV and ENSO phenomena.

Adaptation to DCV Information

DCV information potentially informs on systematic changes in yields which may be adjusted through crop mix selection and other means as illustrated in Figure 1. We consider the crop mix reallocation in the face of DCV and ENSO information and its crop yield, output and revenue distribution effects.

We consider the crop portfolio reallocation and evaluate the economic decision adaptation to the DCV and ENSO effects. There are varied sizes and directions of DCV effects, given different ENSO phenomenon, on crop yield, output and revenue distributions. The DCV phenomena do not only have direct effects on crop yield, but also indirect effects via temperature, precipitation, drought, and their extreme events.

Figure 1: Economic adjustment for climate effects



The ability to adapt to the different climate and weather scenarios could be reflected in the farmer adaptation and price adjustment processes. The economic adjustment processes are agricultural adaptation of farmers from portfolio reallocation and market equilibrium trajectory of crop price adjustment.

The output impacts are different from the yield impacts, because of the farmer altering their crop inputs and mix of crops. The farmers can modify their crop inputs and mix of crops such as land allocation to adapt crop portfolio to different natural scenarios by utilizing the climate and weather forecasting information. Thus, the impacts on output could be different to the impacts on crop yield because of farmers adapting their agricultural economic resource allocation.

Similarly, the effects of DCV on revenue are different from the output impacts from price adjustment reflecting the scarcity or magnificence of crop output. The mixture of output levels will further become an important factor in competitive market mechanism through price adjustment process by production and consumption choices from economic agents, where output prices reflect scarcity or magnificence of crop output.

This price adjustment process from quantities demanded and supplied will determine producer revenue as the value of crops produced, such that the climate and weather effects through agricultural adaptation and market adjustment would change the revenue loss or profit. The value of adapting to DCV information would be reflected in more valuable crop mixes and in turn better decisions for higher profitability.

Transition Probabilities

We have eight possible mutually exclusive combinations for the DCV phase combinations. The incidence of these DCV combinations between 1950 and 2012 is considered as a separate scenario of each combination in any given year. In each case, we acknowledge that each DCV-phase combination dominates the impacts of the weather and the occurrence of extreme events and climate anomalies which can be attributed only to this particular phase combination.

Assuming that patterns in climate that occurred in the past will occur again with the similar relative frequency in the future, we construct one year transition probabilities between DCV phase combinations by looking at the historical chance of transition from a given DCV phase combination today to another phase combination next year. Such information will be used as the conditional probability given today phase combination to the one in the next year. Information on such transitions and associated yield implications could help farmer adaptation. The transition probabilities are given in Table 28.

Framework on Adaptation in Responding to DCV Information

Now we discuss an estimation procedure for the utilization of DCV information. To do this we consider the profit consequences of a crop mix shift by computing how expected net profit by crop is shifted by DCV phase combinations. To construct profit we use the regression estimate of revenue minus a cost estimate drawn from USDA NASS estimates of production cost per planted acre for 2011-2012[7] (USDA-NASS. 2013).

In doing this we rely on the basic theory of profit maximization. We denote $CI_{i,dcv,enso}$ as the estimated net profit for the 5 crops (i) under the 8 DCV phase combinations (*dcv)* and the 3 ENSO phases *(enso)*. Given the information set Ω, we assume the farmers choose to allocate land to crops with the corresponding crop portfolio net income being $NI_{\omega,dcv,enso}$ given the crop mix choice ω from the production function f(y) for $NI_{\omega,dcv,enso} = \sum_i w(i) * CI_{\mathrm{i},dcv,enso}$ where *w(i)* is area of harvested acres for crop i.

We denote $\boldsymbol{\pi}_{\Omega}$ as the expected net profit of crop under the historical frequency case and $\widehat{\boldsymbol{\pi}_{\Omega^*}}$ as the expected net profit when the forecast is under the transition probabilities case, given the historical DCV and ENSO frequencies $p_{dcv,enso}$, and the

[7] The operating cost includes seed, fertilizer (commercial fertilizers, soil conditioners, and manure), chemicals, custom operations (including technical services and commercial drying), fuel, lube, and electricity, repairs, purchased irrigation water, and interest on operating capital. Allocated overhead includes hired labor, opportunity cost of unpaid labor, capital recovery of machinery and equipment, opportunity cost of land (rental rate), taxes and insurance, and general farm overhead.

forecasted DCV and ENSO possibilities $\hat{p}_{dcv,enso}$. So we have the comparable decision scenarios:

$$\boldsymbol{\pi}_{\Omega} = \max_{\omega \in f(y|\Omega)} \sum_{dcv,enso} p_{dcv,enso} \times NI_{\omega,dcv,enso}$$

$$\widehat{\boldsymbol{\pi}}_{\Omega^*} = \max_{\omega \in f(y|\Omega^*)} \sum_{dcv,enso} \hat{p}_{dcv,enso} \times NI_{\omega,dcv,enso}$$

where the decision choice ω is adjusted to reflect the *dcv* and *enso* scenarios given the information set about the weather and climate situations and their corresponding consequences.

Therefore, the expected value from forecasted information Ω^* relative to the historical frequency information Ω is the aggregated difference between the expected net profits under historical frequency $\boldsymbol{\pi}_{\Omega}$ and the expected net profit under the transition probabilities $\widehat{\boldsymbol{\pi}}_{\Omega^*}$.

Given expected income for a crop production under the transition probabilities exceeds that without them, then adaptation would potentially involve increasing that crop (naturally considering all the crops and picking the best ones) and the converse for crops with negative information gains. Thus, given the transition probabilities and yield forecasts coupled with the DCV phase combination transition probabilities, forecasting information could help the farmers to adapt to the DCV phenomena given ENSO scenarios. For each DCV and ENSO scenario (24 scenarios in total), we compare the estimated average means of profit using historical DCV and ENSO phenomena probabilities and of transition probabilities.

We use expected profit per acre calculated from each DCV and ENSO scenario to construct the comparison of different information situations. Information regarding certain event(s) could be associated with either a positive or negative outcome, under uninformed practice. An economic agent responses to information under assumption that agent reacts rationally to the information.

Agricultural Adaptation from DCV Information

Corn, soybeans, and wheat are crops that generate the highest per acre revenue and profit (Table 26). These three crops utilized most of the land harvested and also produced of the largest percentage shares of revenue and with highest profit margins.

Crop Adaptation

Given a forecast of each DCV phase combination, there are possibilities of crop mix adaptations that will increase gains or reduce losses from producing particular crops. Table 27 shows deviations of estimated profit for each DCV and ENSO scenario from the weighted DCV averages of estimated profit. In the (PDO+,TAG-,WPWP-) phase combination, reducing planting of sorghum would reduce losses, while increasing any other crops especially corn and wheat would increase profits. Similarly, reducing cotton planting in the (PDO-,TAG+,WPWP-) phase combination could reduce the harmfulness from this phase combination. Both these first two discussed DCV phase combinations have positive impacts on other crops. The land saved from sorghum in the (PDO+,TAG-,WPWP-) phase combination and cotton in the (PDO-,TAG+,WPWP-) phase combination could be allocated to the higher profit margin crops such as corn, soybeans, and wheat.

For the (PDO-,TAG-,WPWP+) phase combination, all the crops would have reduced profits from this particular weather and climate scenario. The deviation of expected profits from their DCV-phase combination weighted average is small in percentages but rather high in term of monetary value. The higher-revenue-generated crops tend to suffer more from the larger sizes of reduction in their expected profits. The most damaged crop is corn which has atmospheric expected loss for about 195 million dollars in the (PDO-,TAG-,WPWP+) phase combination averaged over ENSO scenarios. The next top three negatively affected crops are soybeans and wheat which have losses of 61 and 49 million dollars, respectively. The total loss in the (PDO-,TAG-,WPWP+) phase combination is 309 million dollars on average among ENSO phases.

In the (PDO-,TAG+,WPWP+) phase combination, the investments in wheat would be expected for lost. The loss size is around 30 million dollars, which this reflects in aggregated loss of all crops for about 1 million dollar on average of ENSO scenarios. Similarly, in the (PDO+,TAG+,WPWP+) phase combination, the soybeans production is estimated to have negative profit, but the loss is negligibly very small. Lastly, the (PDO+,TAG-,WPWP+), (PDO-,TAG-,WPWP-), and (PDO+,TAG+,WPWP-) phase combinations have positive expected net profit for all crops in this study with annual values of 141, 106, and 85 million dollars, respectively.

As we can find gain from (PDO+,TAG-,WPWP+), (PDO-,TAG-,WPWP-), and (PDO+,TAG+,WPWP-), we should allocate land for corn, soybeans, and wheat which provide highest profit margins. Particularly, Table 27 shows that increasing corn in some specific DCV phase combinations which the (PDO-,TAG+,WPWP-), (PDO+,TAG+,WPWP-), (PDO+,TAG-,WPWP+), and (PDO+,TAG+,WPWP+) phase combinations would provide substantial opportunities for profit gains.

Agricultural Economic Decisions in Regard to Climate and Weather Scenarios

Now we discuss the adaptation possibilities. We consider the average profit per acre given DCV information in contrast with the average profit per acre without DCV information, and the same for harvested acres. Using the transition probabilities provided in Table 28, we compute the expected profit per acre with the DCV information and their corresponding harvested acres using the same transition probabilities.

We calculate the average gain and loss from the differences in average profits per acre between with and without DCV information *multiplied* by the differences in harvested acres with and without DCV information. We report these in Table 29. They could be positive or negative depends on the directions between differences of expected profits per acre and their corresponding differences of expected harvested acres. If both changes move on the same direction, which means the acres increased as the profit per acre increased, or the acres decreased as the profit per acre decrease; thus positive gain. On the other hand, if the changes move on the opposite directions, this results in negative gain.

Theses provide framework for adaptation possibilities. We derive the condition between the expected profits without knowledge and in transition probability case where increasing acres of a crop makes sense. For example, the expected profit per acre under the transition probability case exceeds that under the without information case, while there are increasing acres, thus adaptation directions provide gain from having more information. On the other hand, the expected profit per acre under without information is higher than under the transition probability case implies correspondingly decreasing the harvested acres would get a gain.

As shown in Table 29, we find that the adaptation possibilities occur in most of the DCV phase combinations in which the historical DCV weighted average of ‘difference in expected profits per acre’ multiplied by ‘difference in expected acre’ would result in expected aggregate positive gain.

We also find that the farmers could have a gain for aggregate expected profits adaptation from all DCV phase combinations but not for (PDO-,TAG+,WPWP-) and (PDO+,TAG+,WPWP-). The loss in aggregate expected profits from all crops in the (PDO-,TAG+,WPWP-) phase combination is quite large, majorly due to the inefficient adjustment in corn.

These are DCV phase combinations that in some crops the misdirection of adaptation occurred, which resulted in negative gains. These losses occur from the expected profit per acre differences and the expected harvested acre differences do not adjusted with the same directions. For example, the differences in expected profit per acre are positive when the differences in expected harvested acre are negative, or vice-versa.

Consider the average of expected gain or loss for each crop from the three ENSO phases, there are negative gain for corn in (PDO-,TAG+,WPWP-) and (PDO+,TAG+,WPWP-); cotton in (PDO+,TAG-,WPWP-); sorghum in all DCV phases but (PDO-,TAG-,WPWP+); soybeans in (PDO-,TAG+,WPWP-) and (PDO-

,TAG+,WPWP+); and wheat in (PDO+,TAG-,WPWP-), (PDO+,TAG+,WPWP-), and (PDO+,TAG+,WPWP+).

Therefore, the compensations of positive and negative gains in any given DCV phase combination from all crops provide the aggregate expected profits for that particular DCV phase combination. Even the negative gains of aggregate expected profits occur in (PDO-,TAG+,WPWP-) and (PDO+,TAG+,WPWP-), the DCV weighted average of gain and loss from adaptation possibilities provide the expected positive gain which indicates the rational adjustment of farmers.

These results provide the basic framework on crop mix adaptation in adjustment to DCV phenomena. The similar consideration for adaptation possibilities could be applied in a given ENSO phase, when the forecasted information is available.

Conclusions

This study investigates how decadal climate variability (DCV) impacts major US crop yields and their distributions. The study is done over 48 US states and the period 1950-2012. To the best of our knowledge, no one has studied the effects of DCV phenomena on US crop production at the national level before.

We compute the total DCV effects from the direct effects of DCV phenomena on yield and their indirect effects via the effects on weather variables and in turn the weather effects on yield. We find that the DCV phenomena have statistically significant effects on weather and yield and that certain phase combinations regionally alter yields of the US major crops with both positive and negative results on major crop yields. We also find the direct DCV effects are mostly larger than the indirect DCV effects. If there are both direct and indirect effects on a DCV phase combination in a specific region, mostly both the effects have the same direction on crop distribution moments especially on variance, skewness, and kurtosis.

We find almost insignificance of DCV effects at national level. However, there are regional impacts on yield distributions. At the regional level, we find DCV phase combinations have differential impacts on crop yields across regions of the US. Negative impacts occur on major crops in regions such as Central for corn; Southern Plains for cotton; Northern and Southern Plains for sorghum; Central, Northern Plains, and Southern Plains for soybeans; and Northern Plains and Pacific for wheat. On the other hand, there are also major positive impacts on sorghum in Southern Plains especially under (PDO-,TAG+,WPWP+) phase combination. We also find how DCV affects crop yields, temperature, rainfall, and drought. Where our analysis overlaps the Mehta et al. (2011, 2012)'s Missouri River Basin study, we examined the consistency of our results and found we develop similar findings on weather and crop yields effects.

The regional DCV effects on crop distribution higher-moments vary by crops. The DCV phase combinations could alter variance, skewness, and kurtosis of yield distributions for most important crops such as corn, soybeans, and wheat in their some major producing regions such as Central, North Plains, and Southeast for corn; Northern Plains and Central for soybeans; and Northern Plains, Mountains, and Central for wheat.

For corn, we find that (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) reduce variability in the Central region. but the (PDO-,TAG+,WPWP+) increases in Southeast. For soybeans, the (PDO-,TAG+,WPWP+) decreases soybeans yield variability in the Central region. For wheat, the (PDO+,TAG+,WPWP-) increases yield variability in the Central region, but the (PDO-,TAG+,WPWP+) decreases in the Central region. The (PDO-,TAG+,WPWP-) increases variation in wheat yield for the Mountains region.

In term of skewness, its increases imply the longer right tail and more concentrated mass of distribution of the left of the distribution, thus relatively more of lower values. For soybeans, the (PDO-,TAG+,WPWP+) increases skewness in the Central, the major region that produces soybeans. On the other hand, the (PDO+,TAG-,WPWP-) reduces soybeans yield skewness in the Northern Plains region. For wheat, the (PDO-,TAG+,WPWP-) increases skewness in the Central region, but the (PDO+,TAG+,WPWP-) reduces in the Central. Both the (PDO-,TAG+,WPWP-) and (PDO+,TAG-,WPWP+) phase combinations reduce the wheat yield skewness for the Mountains region.

In term of kurtosis, lower kurtosis means a low distribution with fatter tails in which higher probability under the two-sided areas of tails implies higher chance of vulnerability. For corn, the (PDO-,TAG+,WPWP+) increases kurtosis in the Southeast. For soybeans, the (PDO-,TAG+,WPWP+) decreases kurtosis in the Central. The (PDO+,TAG-,WPWP-) increases yield kurtosis in the Northern Plains. For wheat, the (PDO-,TAG+,WPWP-) reduces kurtosis for the Central, but the (PDO+,TAG+,WPWP-) increases in the Central. Both (PDO-,TAG+,WPWP-) or (PDO+,TAG-,WPWP+) phase combinations increase kurtosis for the Mountains.

While we find that DCV phenomena could alter crop yield distributions at the national level, we find ENSO effects are larger in magnitude. ENSO and DCV have some significant effects on higher yield distribution moment The ENSO effects tend to uniformly alter mean, variance, and skewness of national crop distributions. But DCV effects depend on phase combinations, and their effects could vary in different ENSO phases.

We do an investigation on crop mix adaptation seeing whether farmers can improve welfare given a DCV forecast. We find there are adaptation possibilities involving farmer reallocation of crop mixes given information on DCV phase combinations. This indicates that there is value in disseminating information on DCV forecasts and their expected consequences on crop production.

Limitations and Further Research

This section discusses limitations of the studies and proposes possibilities of future research as follow.

- The jet streams of the North American continent are fast moving ribbons of air high up in the atmosphere which affect precipitation and temperature. For example, Thompson (1988) and Currie et al. (1990) found evidence of effects of jet stream shifts on agriculture in the American Corn Belt. Thus, the including the dynamics of jet streams (e.g. strong horizontal temperature contrast which drives jet formation) could possibly improve the explanation of the observed DCV impacts.

- We can include variation in solar radiation on yield mean regressions as in Grassini et al. (2011) and Sacks and Christopher (2011).
- The analysis does not distinguish yield effects on irrigated and non-irrigated crops. Future research could incorporate the effect of irrigation as an explanatory variable as in some previous studies (Schlenker, Hanemann, and Fisher 2005; Park 2012).
- Instead of separate estimations of the two equations, we can possibly investigate DCV impacts using structural model techniques such as simultaneous equations.
- For count data on number of hot days and highly precipitation days, we take into account their distribution asymmetry using a Poisson-family regression. However, for continuous data on temperature, we didn't control for skewness. Note that we found no statistically significant skewness for precipitation and drought. This could be improved.
- The study could be done at the county level data as in Deschênes and Greenstone (2007, 2012) to study impacts of a finer scale.
- A limited set of years was used to study the effects from decadal climate phenomena and better estimates might arise under a longer period of study.
- It could be beneficial to study the link between climate change and DCV effects.
- Economic adaptation possibilities are based on estimated mean for a given DCV and ENSO scenario. Future work could consider risk attitude.
- Future work should consider use of optimization models to do a better job of examining adaptation in the allocation of farm resources.

CHAPTER III

SUGAR-SWEETENED BEVERAGE DEMAND OF LOW-INCOME FAMILIES

Background

The prevalence of obesity in the U.S. has increased substantially over the past three decades (Smith et al. 2010; Zhen et al. 2011). Currently, two-thirds of adults and one-third of children are either obese or overweight, with higher rates in low-income populations. Obesity and its consequences are economically expensive; the US spent $147 billion or almost 10% of national health care dollars to treat the consequences of obesity in 2008. Half of these costs were paid by the public sector through Medicaid and Medicare (Finkelstein et al. 2009).

Sugar-sweetened beverages (SSBs; beverages containing added caloric sweeteners) have been shown to be a contributor to obesity and the costs obesity imposes (Malik et al. 2006). In turn, taxes on these beverages have received considerable policy attention as a vehicle for reducing SSB negative effects. Government action to reduce excessive SSB consumption can be justified on economic grounds. Market failures related to SSB consumption include excessive consumption due to imperfect information on the health consequences of over-consumption, consumers' preference for short-term gratification despite long-term harm (myopic behavior), and externalities as consumers do not bear the full cost of their consumption decisions (usually reflected in high public health care costs, disability payments, and lost productivity). Schwartz and Friedman (2012) argued that SSBs should be a primary focus of obesity prevention campaigns as the indicated research linking SSBs to obesity and other negative health outcomes is stronger than for any other beverage or food. Low-income populations are most affected by excessive SSB consumption and diet-related illnesses (Brownell et al. 2009). In turn a number of studies (Brownell and Frieden 2009; Brownell et al. 2009; Andreyeva, Chaloupka, and Brownell 2011; and Schwartz and Friedman 2012) argue that taxes that increase the cost of SSBs and shift consumption patterns from SSBs to non-caloric or low-calorie beverages would benefit both society and economically-disadvantaged groups. In addition, the tax revenue could be further directed towards improving nutrition of low-income families.

The precise effects of SSB taxation on beverage consumption are ambiguous in part due to uncertainty about patterns of beverage substitution. For example, a tax-induced price increase could encourage some consumers to shift away from SSBs to fruit juices or milk (which would not be taxed, but which have similar caloric content), and might have little to no effect on total caloric intake. On the other hand, consumers could shift to diet beverages or water, which would reduce their caloric intake. Finally, some consumers could increase purchases of sugary foods to compensate for the reduction in SSB sugar intake. The total net effect of SSB taxation on caloric intake is currently unknown, and further work is necessary to understand substitution patterns when SSB prices change. This paper undertakes a study of substitution patterns and caloric intake consequences in the context of participants in the federal food assistance programs.

The Supplemental Nutrition Assistance Program (SNAP) provides food purchase assistance to low income families to alleviate hunger and malnutrition in these populations (Leftin and Strayer 2011). SNAP benefits can be used to buy virtually any food or beverages, excluding alcohol, hot foods and some ready-made foods (SNAP 2011). In FY 2013, the U.S. Department of Agriculture provided an average of $133.79 per month to 47.7 million SNAP participants or about one in every seven Americans (FNS 2013).

There are debates regarding the SNAP role in affecting nutrition and obesity (Just 2006). Critics argue that SNAP encourages unhealthy eating (SNAP to Health 2013), and that SNAP provides incentives to buy cheaper foods of minimum nutritional value (CSPC 2012; Andreyeva et al. 2012). At the same time, some research indicates that accesses to SNAP benefits do not result in increased obesity (Ver Ploeg et al 2006; Ver Ploeg and Ralston 2008). Additionally, Guthrie (2007) concluded that SNAP participation improves food choices of low-income participants.

Other research indicates that, compared to income-eligible nonparticipants, SNAP participants have less nutritious diets (Ver Ploeg et al. 2006; Ver Ploeg et al. 2007; Ver Ploeg and Ralston 2008; Leung et al. 2012; Leung et al. 2013) and consume at least 40% more SSBs than other consumers (Shenkin and Jacobson 2010). At the national level, SNAP funds paid for approximately $1.7-2.1 billion per year for SSBs in grocery stores (Andreyeva et al. 2012).

Taxation of SSBs has been studied particularly given the tight budget of lower-income people. Lin and Guthrie (2007) used examples drawn from previous research to investigate whether low-income SNAP participants had different price responses compared to other consumers. They concluded that responsiveness to price changes varied by type of food and household income with higher price elasticity among low-income households. Huang and Lin (2000) suggested that food stamp price manipulations might have varying effects across different food categories with certain categories like nutrient-rich foods such as dairy, fruit, and vegetables being responsive. Zhen et al. (2011) found that demand for SSBs among low-income households was less elastic to own-price changes and less substitutable as compared to higher-income households.

A number of economic studies on SSBs focused on cross-price effects to investigate substitution interrelationships (Yen et al. 2004; Fletcher et al. 2010; Smith et al. 2010; Zhen et al. 2011; Dharmesana and Capps 2012). Only a few of these studies focused on low-income people (Yen et al. 2004; Zhen et al. 2011). Fletcher et al. (2010) found that taxation could reduce soft drink consumption but would increase consumption of other caloric beverages, such as milk and juice, resulting in no significant difference in calorie intake. Smith et al (2010) found that a 20% tax on SSBs would encourage consumers to reduce SSB consumption in favor of non-taxed beverages. Dharmesana and Capps (2012) found that consumption of regular soft drinks, sports drinks, and fruit drinks would be negatively impacted by the proposed tax. Zhen et al. (2011) found a tax of a half-cent per ounce would reduce SSB consumption for both low- and high-income households. Finally, Yen et al. (2004) found that whole milk, reduced-fat milk, juice, coffee, and tea were net substitutes for soft drinks. Smith et al. (2010) categorized beverage purchases by caloric content, with all SSBs combined in one category of caloric sweetened beverages. However, the own-price elasticities of different SSBs may vary, and SSBs may also be interrelated. Dharmasena and Capps (2012) had richer delineation that classified SSBs and non-sugary beverages into several categories. Table 30 provides a list of beverages examined in earlier research.

To the best of our knowledge, none of the earlier SSB demand analysis studies factored in the different types of payment used plus narrowed in on low-income households. The objective of this study is to compare the responsiveness of federal assistance program participants to SSB price changes considering different forms of payments. This will be done by considering the own-price and cross-price elasticity of beverage purchases. Specifically, we compare the price responsiveness of SNAP participants purchasing beverages using SNAP benefits and using non-SNAP funds along with the price responsiveness of non-SNAP participants using private fund and with all WIC participants using WIC benefits.

We will carry out this study based on grocery store scanner data of nonalcoholic beverage purchases from a regional supermarket chain in New England. The data set covers purchases by 47,705 households with 1,802,714 beverage-purchased transactions in 58 chain stores in Connecticut and Massachusetts during January 2009-June 2011. A unique feature of this data is the identification of the source of funds used to pay for every purchase. This includes SNAP benefits, WIC benefits, and personal funds. We will consider them in aggregated setting at store level on the monthly basis for different types of assistance program participants and types of payment.

Theoretical Model

Many demand models have been used in the literature. We use the Quadratic Almost Ideal Demand System (QUAIDS) model developed by Banks et al. (1997) due to its flexibility in estimating the price effects and allowing the use of a quadratic form of price responses in the expenditure share specification (as discussed in Dharmesana and Capps 2012).

In QUAIDS the demand expenditure shares are linear in parameters on the set of log prices with a nonlinear functional form of real expenditures as follows:

(1) $$w_i = \alpha_i + \sum_{j=1}^{11} \gamma_{ij} \ln p_j + \beta_i [\ln m - \ln a(\mathrm{p})] + \frac{\lambda_i}{b(\mathrm{p})} [\ln m - \ln a(\mathrm{p})]^2 + \varepsilon; i = 1, 2, \ldots, 11$$

where w_i is the budget share of the i^{th} good; p_j is the price for the j^{th} good; m is the level of total expenditures, ε is a random disturbance assumed to have a zero mean and constant variance, and $\alpha_i, \gamma_{ij}, \beta_i, \lambda_i$ are parameters to be estimated. The results of estimations using equation (1) provide interpretable effects of beverage prices and real total expenditure, in quadratic terms, on consumption by demand category.

The above total expenditures extended to permit non-linear Engel curves are in real term by the two price aggregators. For the price aggregators in the model, $\ln a(\mathrm{p})$ is a translog price aggregator:

(2) $$\ln a(\mathrm{p}) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j$$

and $b(\mathrm{p})$ is a simple Cobb-Douglas price aggregator:

(3) $$b(\mathrm{p}) = \prod_{i=1}^{n} p_i^{\beta_i}$$

In estimating the QUAIDS model, we impose the theoretical restrictions of homogeneity and Slutsky symmetry following Banks et al. (1997). These include adding-up restrictions equation (4) plus homogeneity and symmetry properties of microeconomic demand theory are satisfied as in (5) and (6).

(4) $$\sum_i \alpha_i = 1; \sum_i \gamma_{ij} = 0; \sum_i \beta_i = 0; \sum_i \lambda_i = 0$$

(5) $$\sum_j \gamma_{ij} = 0$$

(6) $$\gamma_{ij} = \gamma_{ji}; i \neq j$$

Given these restrictions, equation (1) is a demand system that is added up to one for total expenditure shares ($\sum w_i = 1$), which is homogeneous of degree zero in price and expenditure and satisfies the Slutsky symmetry.

Banks et al. (1997) shows the straightforward method to derive the price elasticities from the QUAIDS model which started from the differentiation with respect to log of total expenditure and prices:

(7) $$\mu_i = \frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(\mathrm{p})}[\ln m - \ln a(\mathrm{p})]$$

(8) $$\mu_{ij} = \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i(\alpha_j + \sum_k \gamma_{jk} \ln p_k) - \frac{\lambda_i \beta_j}{b(\mathrm{p})}[\ln m - \ln a(\mathrm{p})]^2$$

The budget elasticities are given by $e_i = \mu_i / w_i + 1$. The uncompensated price elasticities are given by $e_{ij}^u = \mu_{ij} / w_i - \delta_{ij}$ where δ_{ij} is the Kronecker product. The compensated elasticities are $e_{ij}^c = e_{ij}^u + e_i w_j$ derived from the Slutsky equation.

This demand structure (at least, implicitly) imposes a weak separability assumption which implies that commodities can be partitioned into a number of "separate" groups, where a change in price of a commodity in one group affects the demand for all commodities in another group in the same fashion. Under weak separability, the ratio of marginal utilities from goods within one group is independent relative to the change in consumption of a good in another group (Lusk et al. 2011). For example, consumer demand for a certain beverage entails separability from other food and non-food categories through the price indices of aggregated product groups as a multistage decision process, in which a price change for a product in one group would affect all beverages in the same category in the same way via a price index mechanism. Similar to a demonstration by Goldman and Uzawa (1964), a direct result of weak separability is that price effects from outside a particular beverage group are translated through income effects.

Empirical Specification

Data

The study is based on scanner data of 3,827,707 beverage product purchases. Between January 2009 and June 2011, there were 47,705 loyalty cards with their 1,802,714 purchase transactions. More details are discussed in Andreyeva et al. (2012). Data were only obtained for those who participated at some point in the Special

Supplemental Program for Women, Infants, and Children (WIC). The chain has a loyalty card system and about 90% of all purchases use that card. The loyalty card data are used with each card assumed to come from one household. The data were just on purchases so that no information was available on socio-demographic characteristics.

The data has complete information about all purchases made using each card, such as products and amounts purchased and prices paid. Every purchase was also linked to a payment method, which can include: (a) SNAP, (b) WIC, (c) cash assistance benefits, and (d) personal funds (e.g. cash, credit cards). The use of SNAP, WIC and/or cash assistance benefits indicates participation in the respective program at the time of the purchase. Program participation is assessed based on multiple purchases during each month of the analysis.

Sample

The sample is only on those loyalty cards that made purchases under the WIC program and thus covers only low-income young families with children. Specifically, the data covered WIC participants with at least one WIC purchase in the sample period with the data beginning as of that purchase. Thus purchases prior to joining the sample were unavailable. The data panel is unbalanced as not all participants were all represented in all periods due to timing of first purchase and uneven use of grocery stores.

This study describes supermarket purchases of a variety of non-alcoholic beverages, including SSBs, among WIC- and SNAP-participants, including the use of federal food assistance and nutrition programs. To understand the impacts of tax on different groups of these low-income young families with children, WIC households were differentiated into the following groups by their historical records of beverage purchases: (1) SNAP participants purchasing beverages using SNAP benefits, (2) SNAP participants purchasing beverages with non-SNAP funds including cash, credit cards or EBT cash assistance, (3) non-SNAP participants using personal funds/cash assistance to buy beverages, and (4) all WIC participants using WIC payments, which can only be used to buy milk or 100% juice. The SNAP or non-SNAP participants based on loyalty cards are identified by their historical purchases of whether their purchases on any items in this grocery store chain were made by SNAP benefits or not. These groupings are not mutually exclusive for households, but they are for their transactions, at least by percentage of payment types. As some beverage-purchased transactions can have multiple payment types in one transaction, these transactions were separated by their percentages of payment types. In other words, the four groupings are for transactions depending on the type of payment used in each transaction (e.g., SNAP benefits). These are assumed to represent typical purchasing behavior of participants as in (1) through (4). Table 31 describes numbers of loyalty cards by assistance programs participation and payment types.

Data Aggregation

We considered the cost per ounce and the quantity in ounces for beverage type. We aggregated data by store and month for each of the four household-transaction types. There are 58 grocery stores for 30 months. To avoid empirical difficulties in dealing with zero purchases, we aggregated the data to monthly data for each store-location/month by taking weighted averages of brand-level beverage purchases. Thus, the unit in model estimation is monthly aggregated by store location. The sample sizes are (1) 1,620 based on 57 stores for SNAP participants using SNAP benefits, (2) 1,625 based on 58 stores for SNAP participants using private fund, (3) 1,633 based on 58 stores for non-SNAP participants using private fund, and (4) 1,618 based on 57 stores for WIC participants (SNAP or non-SNAP participants) using WIC benefits. We also have the monthly aggregated stores from all samples which has sample size as 1,643 from 58 stores for comparison.

By each beverage for each participant-transaction types, the calculation on scanner data was carefully done by straightforwardly collapsing the expenditure, volume quantity, and price over store locations and months. The data incompleteness occurred since this beginning of data aggregation for each beverage category due to the missing values from volume quantity and expenditure must be positive at the same time to construct unit price at transaction level.

Fisher Ideal Price Index

In demand analysis with cross-sectional data, prices are generally assumed to reflect "quality" effects which should be corrected before estimation. Cox and Wohlgenant (1986) argue that the factors of cross-sectional price variation must be identified, and the price variation induced by region and season is desirable. Also, the quality differences caused by heterogeneous commodity aggregates are the other source of the cross-sectional price variation that may be problematic to the estimation of demand functions which could result in biased and misleading demand elasticities.

Therefore, quality-adjusted prices should be used to estimate demand functions using cross-sectional data.

As discussed in Zhen et al. (2011), there is a possible endogeneity bias from the quantity-quality trade-off by consumers and using a unit price straightforwardly calculated as the ratio of expenditure to volume. To avoid this problem, we used Fisher ideal price index at the brand level (Zhen et al. 2011, 2013) which is an approximate way of dealing with substitution bias (Hausman 2003) and applying brand-specific quantity weights to develop a price index for each beverage category. This approach is similar to the Bureau of Economic Analysis methodology to compute official price indexes (Abel et al. 2007). Similar to Zhen et al. (2011), as each beverage category includes a large number of unique brands, and many with a very small market share, we attempted to reduce the number of brands in each price index. To do so, we first identified brands with at least 0.5% of the market share in total beverage sales during the study. All store brands were aggregated into one private-label brand. Other brands with less than 0.5% of the market share in total beverage sales were aggregated into one composite brand. The brand-level prices were calculated as the ratios of expenditure and purchased quantity. We calculated a weighted average of brand-level prices for each store-location. The base brand-level prices and quantities in the Fisher ideal price indices are averages over the sample period in this scanner dataset. Therefore, values of the price indices vary across markets as well as overtime as the quality-adjusted prices.

Data Imputation

We perform the price imputation at the purchase scanner data level separately for each dataset which are SNAP participants using SNAP benefits, SNAP participants using private payment, non-SNAP participants using private payment, all WIC participants using WIC, and all household-transactions using all payment types. This micro-data level imputation is done by brand, location, and time for each beverage category. The price we used is the net price after coupons and discounts per ounce which equals to purchasing expenditure divided by quantity in ounce. To impute unobserved (missing) values of price data for each beverage category, we implemented the following imputation process at brand-level. Following Perali and Chavas (2000) and Zhen et al. (2011), we regressed the observed brand-level prices on time, store location, and brand. All regressions were estimated using the robust heteroskedasticity-consistent estimator of the variance-covariance matrix. The regression model was fit to available data and the estimated parameters were used for an out-of-sample prediction to replace missing values.

Beverage Categorization

In this study, we focus on substitution and complementarities of beverages using the extensive categories compared to those assessed in prior studies. We categorized beverages into the following groups: regular (sugar-sweetened) soda, diet soda, 100% juice, fruit drinks, energy drinks, sport drinks, bottled water, flavored water, ready-to-drink (RTD) tea, whole milk, and reduced-fat, low-fat or skim milk (combined into one category of lower-fat milk). We excluded RTD coffee due to few purchases of this beverage. Thus, we have regular soda, juice drinks, energy drinks, sport drink, flavored water, and RTD tea as SSBs.

Estimation

We estimated the QUAIDS model with the nonlinear seemingly unrelated regression (NLSUR) approach. We dropped the last equation because of singularity arising when the budget shares sum to one, $\sum w_i = 1$ as discussed in Banks et al. (1997). The parameters from the last equation can be recovered from this system of nonlinear equations:

$$w_i = \alpha_i + \sum_{j=1}^{11} \gamma_{ij} \ln p_j + \beta_i [\ln m - \ln a(\mathrm{p})] + \frac{\lambda_i}{b(\mathrm{p})} [\ln m - \ln a(\mathrm{p})]^2 \tag{9}$$

$$+ a_i t + \tilde{a}_i t^2 + \sum_{j=2}^{4} b_{ij} Q_j + \sum_{k=2}^{58} c_k Store_k + d_i temp; \quad i = 1, 2, \ldots, 10$$

where t is time, Q_j and $Store_k$ are dummy variables for quarters and stores, $temp$ is the average monthly temperature for Connecticut or Massachusetts, and a_i, $\tilde{a}_i$, b_{ij}, c_k, and d_i are the coefficients from the i^{th} equation to be estimated.

We used nonlinear seemingly unrelated regressions (NLSUR) to estimate each demand system separately for different sample groups. After adding-up, homogeneity, and symmetry restrictions were imposed, there were 193 free parameters to be estimated. The parameters of the excluded equation were obtained from the adding-up condition by the Delta method.

We followed Blundell et al. (1993)'s suggestion to include time trend and seasonal dummies to improve the performance in estimation the QUAIDS model with aggregated data. We also associate the spatial heterogeneity in different store locations with the store dummy variables in the estimations. Instead of directly using weighted average of the net price after discounts and coupons per ounce which is simultaneously observed with quantity purchased and expenditure paid at the transactional level, we construct the location-specific Fisher ideal price indices for the eleven beverage categories based on brand-level prices to avoid quantity-quality trade-off issues associated with using unit values (see Deaton 1988; Zhen et al. 2011) and to account for possible differences in prices paid and brand preferences between different locations. As the assumption of homogeneity of degree zero is imposed on the system, it is possible to estimate the parameters of the system when expenditure is endogeneous, thereby obtaining consistent estimators (Attfield 1985).

Empirical Results

Descriptive Statistics

Table 32 presents descriptive statistics for the levels of participant expenditures, volume purchased, average product prices, and share of non-alcoholic beverages for low-income participants using the different types of payment as described above. SNAP participants using SNAP benefits have high SSB consumption both in terms of expenditure and quantities compared to participants using personal funds or non-SNAP participants. The most popular SSBs purchased by SNAP participants using SNAP benefits were regular soda, sports drinks, and RTD tea. Those participants also consume whole milk in similar quantities to those using WIC payments.

Regular soda had the lowest prices among all SSBs and the highest volume purchased. Prices of regular and diet carbonated soft drink were the next lowest except for bottled water. All prices are similar across the participant groups except for energy drinks for SNAP participants using private payment and those for using WIC benefits. Price is highest for energy drinks and exhibits the largest variation in their product options.

WIC Participants using WIC benefits only exhibit a higher price for 100% juice among the participant-transaction groups and whole milk, but a lower price for low-fat milk. This price differentiation for WIC payment is common to find in grocery stores. For the WIC participants, the lower low-fat milk price paid for using WIC benefits leads to higher volume purchased, but that group still buys more whole milk even the higher price paid than the other sample groups. The relative consumption of 100% juice is lower. The descriptive results show that, across all beverages, WIC benefits are mostly spent on milk purchases.

In term of budget share, soda has the highest share despite its low price. Budget shares are similar across the consumer groups for all beverages but energy drinks. The SNAP group buys more cheap sweetened energy drinks. Whole milk and reduced-fat milk had lowest budget shares (which this reflects considerable milk purchases using WIC benefits).

Model Results

The estimated QUAIDS parameters are reported in Tables 33-37. The models estimated have reasonably high R^2 indicating that our model fits the data well. We do not find that homogeneity and symmetry restrictions are rejected by the likelihood ratio based Chi-squared statistics.

The results provide strong statistical evidence that increases in regular soda price could reduce soda consumption. For example, one cent per ounce increases in regular soda price could lead to 2.6% reduction on average in its budget share for SNAP participants using SNAP payments. The significance of second polynomial term in expenditure confirms the quadratic functional relationship which implies non-linear causality caused by the real expenditure term. The estimated coefficients of time trend and its square, temperature of Connecticut and Massachusetts, quarterly dummy variables, and store location dummy variables are mostly not significant, except for some location dummy variables.

Elasticities

Based on the estimated parameters, we separately calculated own-price, cross-price, and expenditure elasticities as reported in Tables 38-42. We find significant effects of own-price for all beverage classes except 100% juice for SNAP participants using non-SNAP payment funds and whole milk for all WIC participants using all types of payment. The elasticities vary by participant-transaction group especially for 100% juice, energy drinks, bottled water and milk. The other beverages have similar own-price responsiveness.

For most beverages, the SNAP participants using SNAP benefits have elastic own-price demand, except 100% juice, whole milk, and low-fat milk. For SNAP participants using private payments, energy drink and bottled water have much lower own-price effects than the other participant-transaction groups. The major findings are:-

SNAP participants using SNAP benefits - Regular soda is the top commodity in terms of own-price responsiveness. The other SSBs are also high. All of their own-price elasticities are around or close to one in their absolute value. The own-price elasticities for 100% juice, whole milk, and low-fat milk are lower but significant (See Table 38).

SNAP participants using private funds - This group has lower own-price responses for energy drinks, bottled water, and whole milk. Their elasticities for the rest of the beverages are mostly similar to SNAP participants using SNAP benefits except for bottled water. Also, energy drink has much lower own-price effects than other groups perhaps due to their higher prices (See Table 39).

Non-SNAP participants using private funds - This group tends to have larger price responsiveness than SNAP participants. All of the own-price elasticities are negative and almost one or greater than one (elastic) except whole milk and low fat milk. Own-price elasticity for whole milk is also larger than other sample groups of SNAP participants (using SNAP benefits or private payment). Bottle water also has high price responsiveness comparing with the SANP participants which have SNAP benefits (See Table 40).

All WIC participants using WIC benefits - We find this group has the largest elasticity (in absolute value) in whole milk and low-fat milk among participant-transaction groups. This indicates that those using WIC payments will majorly purchase milk compared to the other participant-transaction groups. On the other hand, We find the purchase of the 100% juice is not price sensitive again reflecting lower purchase but higher price (See Table 41).

All loyalty cards using any payment types - The price elasticities for all loyalty cards using any payment types are mostly in between of these segregated participant-transaction groups. This pattern is clear for own-price elasticities (See Table 42).

We find small cross-price elasticities for SNAP participants using SNAP benefits varying from -0.22 to 0.16, and non-SNAP participants using personal funds varying from -0.16 to 0.28. However, SNAP participants using private payments had a maximum at 1.3 and a minimum at -1.5. The complementary price effects for WIC had a maximum at 0.26 (only one positive cross-price elasticity) and a minimum at -0.7. These significant cross-price elasticities imply the substitution effects among different beverages, in particular for SNAP participants using private funds.

For expenditure elasticities, we have evidence that there are increases in all beverages if SNAP participants have more SNAP benefits, especially for SSBs such as energy drinks, sports drinks, flavored water, and tea. Soda has considerably smaller expenditure elasticity than other SSBs. SNAP participants also spend less for 100% juice and whole milk if they have more personal income, but spend more on fruit drinks, energy drinks, sports drinks, flavored water, RTD tea, and low-fat milk.

Simulated Effects from Beverage Taxation

To study if the tax policy could reduce SSB consumption for the economically-disadvantaged families, we simulated tax-induced price increase for the three demand systems with eleven beverages of the following groups which have mutually exclusive purchase transactions: (1) SNAP participants purchasing beverages with SNAP benefits, (2) SNAP participants purchasing beverages with personal funds including cash, credit cards or EBT cash assistance, and (3) non-SNAP participants using personal funds/cash assistance to buy beverages. We also provide the results from all loyalty cards using any types of payment on beverage purchases. We cannot investigate the tax simulation for WIC benefits, as this has only whole milk, low fat milk, and 100% juice; not including any sugar sweetened beverages.

To investigate the tax effects of SSBs on consumption, tax burden, and tax revenue, we simulated a scenario in which a half- and one-cent per ounce taxes are levied on store-purchased SSBs - regular soda, fruit drinks, energy drinks, sports drinks, flavored water, and ready to drink tea following Zhen et al. (2011, 2013), Brownell and Frieden (2009) and Andreyeva et al. (2011). We use the estimated demand elasticities, the observed beverage purchases in ounces, and the tax-induced changes in retail price indices to calculate the tax impacts on each of participant-transaction groups.

Using both the estimated own- and cross-price elasticities, we find the supporting evidence that a tax-induced price increase would shift intake from SSBs to non-caloric or low-calorie beverages as in Table 43. The effect of substitution decreases the marginal effects of tax on SSBs consumption. However, the direct effects from tax imposing on SSBs are effectively large enough in reducing overall caloric intake. It is also shown in Table 43 and Table 44 that the largest reduction in volume and caloric intake occur with SNAP participants using SNAP benefits to purchase beverages, compared to the other participant-transaction groups. The effects on volume and caloric intake from imposing a one cent per ounce to SSBs are twice the impacts from half-cent per ounce.

The percentage caloric intake reduction under the tax is substantial (Table 45). Monthly calorie reduction ranges from 7.7-8.8 % for a half-cent per ounce tax and 15.3-17.7 % for a one cent per ounce tax. For all loyalty cards using any payment types, the monthly calorie reduction is 7.7% for a half-cent per ounce tax and 15.3% for a one cent per ounce tax. These results can also be expressed in term of 12 oz can of Coca Cola equivalents. Imposing a half-cent per ounce tax reduces annual caloric intake in a volume equivalent to 140 cans for SNAP participants purchasing beverages with SNAP benefits, 133 cans for SNAP participants using personal funds, 132 cans for non-SNAP participants using personal funds, and 130 cans for all loyalty cards using any payment types.

Table 46 reports the expected tax incidence for the aforementioned participant-transaction groups by each beverage. The beverages with most consumption impact from taxing on SSBs are regular soda and sports drinks. The least impacted SSB from taxing is energy drinks. From Table 47 on total per loyalty card tax burden, the SNAP participants using SNAP benefits have to pay \$5.52 and \$9.36 more per month for beverages under the half-cent and one cent per ounce taxes. The SNAP participants using private payments have to pay \$4.58 and \$7.23 more per month for beverages under the half-cent and one cent per ounce taxes. The non-SNAP participants using private payments have to pay \$4.58 and \$7.37 more per month for beverages under the half-cent and one cent per ounce taxes. In addition, they are \$5.42 and \$9.01 for all loyalty cards using any payment types, which are in between these segregated participant-transaction groups. We conclude that the SNAP participants using SNAP benefits would have a greater tax burden than would the SNAP participants using private payments or the non-SNAP participants using private payments. This is also true in the view on percentage shares of monthly SNAP benefits, of averaged for SNAP participants in Connecticut and Massachusetts.

Table 47 also reports estimated annual tax revenue over the population of SNAP and WIC participants in Connecticut and Massachusetts. This is done using the average monthly enrollments of SNAP and WIC households which in 2013 was 233,171 SNAP households for Connecticut and 498,580 for Massachusetts, and 54,248 WIC households for Connecticut and 119,952 for Massachusetts. In turn using those data with our estimated elasticities, taxing the SSBs could create annual tax revenue for the two states of $98.28 million under a half-cent tax and $161.04 million under a one cent tax.

Conclusions

SSB consumption is a major concern in efforts to reduce the rates of obesity in the U.S., particularly among low-income populations. We investigate the price sensitivity of SSB purchases among low-income families participating in the WIC program. The data set allowed us to partition households via their participation in different food assistance programs. In turn, we compare the price responsiveness of three groups across eleven-beverages, including: (1) SNAP participants purchasing beverages with SNAP benefits, (2) SNAP participants using non-SNAP payment methods (such as private dollars and cash assistance), (3) non-SNAP participants using personal funds as a method of payment for beverages, and (4) all purchases by WIC participants. In addition, we examine all WIC participants using WIC benefits for the three-beverage demand system, including 100% juice, whole milk, and lower-fat milk. We aggregate participant-transaction groups based on types of payment for their purchases into store locations over time.

The results are participant-transaction type dependent. Using scanner data from a regional supermarket chain in New England, we find that low-income participants participating in SNAP using SNAP benefits spend more for SSBs than the other groups.

As SNAP participants tend to use SNAP benefits to purchase more high-caloric beverages, this reflects with higher own- and cross-price elasticities when using private funds than when using SNAP benefits to pay for these beverages. The parameters estimated from a demand system of SNAP participants using SNAP benefits were used to simulate the effects of excise taxes on store-purchased SSBs. Our model projects a reduction in SSB purchases, and thus lower calorie intake from beverages when imposing a tax.

These results imply that changes in beverage prices through tax policy or reduced SNAP eligibility for purchasing SSBs could be an important means of affecting beverage purchases among low-income families, especially SNAP participants and their SNAP-funded purchases. We predict that a SSB tax would reduce total SSB purchases among SNAP participants with an increase in juice, bottled water, and milk consumption and decrease in beverage based calories.

Limitations and Further Research

This study is subject to limitations. First, we cannot explicitly analyze the economic decision and related impacts of switching between different payment types. Also, the data only includes consumers with a recent history of WIC participation, so that the elderly and SNAP families without young children are not part of the analysis. Another issue is that this analysis is based on loyalty cards at one grocery chain and does not represent total household purchases in all retail venues. Furthermore, we do not assess beverage purchases in away-from-home outlets such as fast food or full-service restaurants and vending machines, which Smith et al. (2010) show account for about half of total SSB consumption. Also, we do not take into account that some consumers could increase purchases of sugary foods to compensate for the reduction in sugar intake from SSBs. In addition, this study implicitly assumes beverage prices as independent in demand analysis. It is generally the case in demand system estimation that prices are treated as exogenous. One could use a Wu-Hausman test of endogeneity to sort out whether price or quantity belong on the right-hand side in the demand regressions. Finally, the tax effect was simulated by using the estimated coefficients and elasticities rather than direct modeling of the changes in consumption from price changes.

Future research could address the above limitations and also assess the degree of aggregation bias and information loss resulting from aggregation to the consumer classes. The construction of various groups in the demand analysis has the limitation that the households fall into multiple payment groups thus the payment classes do not identify unique household groups. Further research could also consider consumers switching to non-beverage high-sugar foods as done in Zhen et al. (2013).

Despite these limitations, our study adds value to the literature by evaluating the likely effectiveness of SSB taxes among low-income groups, especially for the participant-transaction group of all loyalty cards using any types of payment on beverage purchases.

CHAPTER IV

CONCLUSIONS

This dissertation examines two main topics as reported in the two main essays using economic analysis supported by different applied econometric techniques. Specifically, the first essay in Chapter II reports on an analysis of:

- The effects of decadal and annual climate variability phases on US mean crop yields, output, and revenue distributions for corn, cotton, sorghum, soybeans, and wheat;
- Possible adaptation strategies given DCV information in the face of climate variability.

In the second essay in Chapter III we analyze:

- The demand elasticities of sugar sweetened beverage purchases among low-income households that used WIC benefits;
- The estimated SSB consumption impacts of a SSB excise tax.

In Chapter II, we investigated DCV impacts by developing and estimating an empirical model to explain the impacts of decadal climate variability (DCV) on major US crop yields and then examined crop mix adaptation possibilities. The DCV effects were estimated using United States state level data from 1950-2012. The crop yield distributions were estimated with the skew-normal regression model allowing estimation of asymmetric yield distributions. We also investigate the indirect DCV effects on crops through DCV effects on the hydro-meteorological variables.

We find significant, regionally differentiated DCV effects on crop yield means, variances, and skewness revealing that DCV phenomena have impacts on US crop productivity. The regional DCV effects on higher crop yield moments vary by crop. The DCV phase combinations could have impacts on variance, skewness, and kurtosis of yield distributions of crops with highest revenue and profit margin. Effects on yield distributions are found on corn, soybeans, and wheat in their corresponding major areas such as Central, North Plains, and Southeast for corn; Northern Plains and Central for soybeans; and Northern Plains, Mountains, and Central for wheat.

ENSO also has significant effects on yield distribution moments. The ENSO effects tend to uniformly alter mean, variance, and skewness of national crop distributions. I also find DCV effects can be heterogeneous across different ENSO phases.

Farmers may exploit DCV forecast information, and their impacts on crops, via crop mix adaptation given information on DCV phase combinations. The results provide evidence that the use of forecasts may permit valuable adaptive responses. Relative to the historical frequency, under the transition probability information, there are potentially beneficial regional acreage expansions or reductions for corn, cotton, sorghum, soybeans, and wheat in response to information on upcoming DCV phase combinations. This indicates that there is value in disseminating information on DCV forecasts and their expected consequences on crop production.

In Chapter III, we examine demand for sugar-sweetened beverage (SSB) consumption among low-income households using WIC program benefits. Using scanner data from a New England supermarket chain with 3.8 million product-level purchases by over 47,000 households, we aggregate them by store level and month. We then have specific types of total purchases using different payment types which are total purchases by (1) SNAP households using SNAP benefits, (2) SNAP households using private funds, (3) non-SNAP households using private fund, and (4) households (SNAP or non-SNAP) using WIC benefits.

We estimate a quadratic almost ideal demand system (QUAIDS) model of eleven non-alcoholic beverages for the total expenditure classes (1), (2), and (3) along with a more limited model explaining only three WIC eligible beverages for expenditures in class (4). The estimation procedure is the non-linear seemingly unrelated regression (NLSUR) method and using the Delta method for estimating elasticities.

The estimated demand system permits study of substitution patterns and caloric intake consequences. We find that purchases with SNAP benefits have higher own-price and cross-price elasticity compared with those purchased with other funds such as cash. We also find changes in beverage prices through tax policy could be an effective means of affecting beverage purchases among low-income households, especially SNAP households and their SNAP-funded purchases.

Both the DCV and SSB research efforts are subject to limitations and can be extended. The DCV analysis does not distinguish yield effects on irrigated and non-irrigated crops as in Schlenker, Hanemann, and Fisher (2005) and Park (2012). Also the analysis could be done at the county level data to study DCV impacts at a finer scale as in Deschênes and Greenstone (2007, 2012). There are possibilities to link DCV effects with climate change, and the future research might consider using more complex the optimization models to examine adaptation possibilities.

The SSB analysis only included data on transactions from WIC participants and only and those stores and thus does not represent total household purchases in all retail venues, included purchases in away-from-home outlets such as fast food or full-service restaurants and vending machines. An extension could be done as in Zhen et al. (2013) which analyzed consumers switching to non-beverage high-sugar foods. Future theoretical research could address a framework for demand analysis to explain consumer behavior with different sources of payment, including restricted public assistance benefits.

We need to admit that the right hand side variables in econometric estimations in both of the substantive dissertation chapters are not set by randomization, but rather are observational; set as outcomes that may show systematic relations amongst one or more of other right hand side variables (See Bessler 2013).

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APPENDIX A

Table 3: Regression estimates for weather variables

	Temp	$Temp^2$	Precip	$Precip^2$	PDSI	$PDSI^2$	Log of Temp Intensity	Log of Precip Intensity
Trend								
	-0.0626***	-6.874***	0.0109	0.504	0.0363**	0.122**	-0.0144***	-0.00170*
	(<0.000)	(0.000)	(0.724)	(0.866)	(0.003)	(0.001)	(<0.000)	(0.033)
Trend^2	0.00126***	0.137***	0.000285	0.0335	-0.000411*	-0.00112*	0.000213***	0.0000275*
	(<0.000)	(0.000)	(0.533)	(0.439)	(0.043)	(0.038)	(<0.000)	(0.022)
El Niño x R1	0.164***	14.37***	-0.660*	-49.60*	-0.434***	-1.448	-0.0539*	-0.0144
	(<0.000)	(0.000)	(0.022)	(0.023)	(<0.000)	(0.076)	(0.018)	(0.081)
El Niño x R2	-0.0292	-5.217	0.478*	17.18*	0.0209	-0.485	-0.0899***	0.0123
	(0.421)	(0.133)	(0.027)	(0.041)	(0.933)	(0.552)	(0.001)	(0.585)
El Niño x R3	-0.0973***	-10.61***	0.403	39.82	0.236*	0.889	0.0838**	0.00956
	(<0.000)	(0.000)	(0.144)	(0.099)	(0.024)	(0.202)	(0.003)	(0.202)
El Niño x R4	0.227*	21.49*	1.018***	43.68***	0.557	2.064	-0.0674	0.0386***
	(0.012)	(0.018)	(<0.000)	(0.000)	(0.153)	(0.073)	(0.164)	(0.001)
El Niño x R5	0.0274	-0.509	0.966***	53.28***	0.420**	1.294	-0.0103	0.00693
	(0.867)	(0.977)	(<0.000)	(0.000)	(0.001)	(0.331)	(0.297)	(0.690)
El Niño x R6	0.0433	5.654	0.469	59.12	0.122	0.267	-0.00523	-0.0124
	(0.227)	(0.177)	(0.405)	(0.322)	(0.190)	(0.728)	(0.801)	(0.436)
El Niño x R7	0.203***	26.71***	1.541**	160.6**	-0.0517	-0.385	-0.00492	0.00627
	(<0.000)	(0.000)	(0.001)	(0.006)	(0.697)	(0.709)	(0.844)	(0.582)
La Niña x R1	0.605***	57.82***	-0.0481	-12.90	-0.571***	-2.053*	0.231***	-0.00575
	(<0.000)	(0.000)	(0.840)	(0.430)	(<0.000)	(0.017)	(<0.000)	(0.620)
La Niña x R2	-0.362***	-34.71***	0.779*	32.14**	1.085***	3.999***	-0.0359	0.0332
	(<0.000)	(0.000)	(0.015)	(0.006)	(0.001)	(0.000)	(0.056)	(0.222)
La Niña x R3	0.172***	15.59***	0.992***	92.10***	0.159*	0.269	0.194***	0.00414
	(<0.000)	(0.000)	(<0.000)	(0.000)	(0.024)	(0.714)	(<0.000)	(0.567)
La Niña x R4	0.156	16.01	1.115*	46.23*	0.946	3.550**	0.0553	0.0572***
	(0.199)	(0.163)	(0.043)	(0.040)	(0.099)	(0.003)	(0.318)	(0.001)
La Niña x R5	-0.465***	-48.21***	3.781***	230.3***	1.463***	4.475**	-0.112*	0.122***
	(<0.000)	(0.000)	(<0.000)	(0.000)	(<0.000)	(0.001)	(0.025)	(<0.000)
La Niña x R6	0.368***	41.25***	0.0262	20.32	-0.136	-0.568	0.101***	-0.0117
	(<0.000)	(0.000)	(0.930)	(0.469)	(0.150)	(0.484)	(<0.000)	(0.108)
La Niña x R7	0.457***	56.75***	-0.967	-79.97	-0.248***	-1.289	0.0708*	-0.0183
	(<0.000)	(0.000)	(0.092)	(0.163)	(<0.000)	(0.236)	(0.041)	(0.338)
C1 x R1	0.319**	27.03**	3.150***	218.2***	0.378	1.381	0.00438	0.0161
	(0.003)	(0.004)	(<0.000)	(0.000)	(0.080)	(0.287)	(0.960)	(0.228)

C2 x R1	-0.104	-14.30*	-1.233**	-72.21*	-0.614***	-2.224	0.00764	-0.0886***
	(0.133)	(0.030)	(0.003)	(0.017)	(<0.000)	(0.082)	(0.947)	(<0.000)
C3 x R1	0.139	3.102	1.997*	158.9*	0.130	0.0408	-0.144	-0.00332
	(0.362)	(0.809)	(0.019)	(0.033)	(0.641)	(0.975)	(0.229)	(0.796)
C4 x R1	-0.611***	-63.29***	0.901	67.35	0.244*	0.0923	-0.172***	-0.0401
	(<0.000)	(0.000)	(0.089)	(0.086)	(0.041)	(0.948)	(<0.000)	(0.119)
C5 x R1	-1.310***	-135.2***	1.639	120.4	-0.107	-1.567	-0.426***	-0.0427
	(<0.000)	(0.000)	(0.285)	(0.322)	(0.742)	(0.464)	(<0.000)	(0.293)
C6 x R1	0.105	-2.705	1.253	78.35	0.295	0.600	0.0299	-0.0195
	(0.466)	(0.811)	(0.050)	(0.130)	(0.238)	(0.663)	(0.799)	(0.050)
C7 x R1	0.572*	46.34*	1.659*	107.1	0.468**	0.511	0.0274	-0.00289
	(0.017)	(0.017)	(0.020)	(0.057)	(0.004)	(0.721)	(0.685)	(0.884)
C1 x R2	0.0884	11.23	0.572	7.869	0.948	4.125**	0.0130	0.0360
	(0.408)	(0.312)	(0.122)	(0.491)	(0.055)	(0.001)	(0.369)	(0.229)
C2 x R2	-0.156	-17.82	-0.824*	0.372	-0.521	-1.863	-0.0840*	-0.0878**
	(0.183)	(0.103)	(0.039)	(0.989)	(0.086)	(0.145)	(0.030)	(0.004)
C3 x R2	0.438***	38.60*	-1.820***	-92.82***	-1.580***	-6.832***	0.139**	-0.104*
	(<0.000)	(0.015)	(<0.000)	(0.000)	(<0.000)	(0.000)	(0.007)	(0.023)
C4 x R2	0.0626	6.782	1.112**	36.88**	1.035*	3.364*	0.0560	0.0572*
	(0.561)	(0.515)	(0.008)	(0.008)	(0.029)	(0.017)	(0.176)	(0.049)
C5 x R2	1.067**	106.8*	-0.630	-58.38	-1.123*	-5.485*	0.252***	-0.0944*
	(0.005)	(0.010)	(0.420)	(0.052)	(0.029)	(0.010)	(<0.000)	(0.048)
C6 x R2	0.314***	21.27	-0.648	-74.77**	-0.511	-3.222*	0.129**	-0.0505
	(0.001)	(0.091)	(0.144)	(0.004)	(0.193)	(0.019)	(0.002)	(0.391)
C7 x R2	0.970***	89.81***	1.417**	6.332	1.164*	4.264**	0.129***	0.0564
	(<0.000)	(0.000)	(0.008)	(0.768)	(0.016)	(0.003)	(<0.000)	(0.228)
C1 x R3	-0.00517	-2.450	-2.218**	-220.5***	-0.800***	-2.882**	0.199*	-0.0429***
	(0.910)	(0.573)	(0.002)	(0.001)	(<0.000)	(0.009)	(0.017)	(0.001)
C2 x R3	-0.227	-29.77**	-1.564**	-165.8**	-0.379**	-0.670	-0.0301	-0.0278*
	(0.055)	(0.010)	(0.008)	(0.006)	(0.004)	(0.544)	(0.716)	(0.014)
C3 x R3	0.174**	9.904	1.326*	102.7	0.328	1.208	0.251**	-0.00409
	(0.010)	(0.098)	(0.030)	(0.087)	(0.138)	(0.287)	(0.002)	(0.760)
C4 x R3	-0.592***	-61.51***	-1.785***	-171.4***	-0.198	-0.591	-0.204*	-0.0547**
	(<0.000)	(0.000)	(<0.000)	(0.000)	(0.166)	(0.623)	(0.030)	(0.009)
C5 x R3	-1.168***	-123.8***	10.14***	976.7***	2.073***	5.706**	-0.594***	0.148***
	(<0.000)	(0.000)	(<0.000)	(0.000)	(<0.000)	(0.002)	(<0.000)	(<0.000)
C6 x R3	0.00418	-9.936	1.547	127.0	0.707**	2.213	0.101	-0.0218
	(0.959)	(0.173)	(0.123)	(0.180)	(0.008)	(0.063)	(0.230)	(0.113)
C7 x R3	0.502***	43.56***	0.758	55.47	0.239	1.019	0.254**	-0.0129
	(<0.000)	(0.000)	(0.451)	(0.557)	(0.273)	(0.406)	(0.001)	(0.301)
C1 x R4	-0.254***	-25.38***	3.645***	174.3**	2.048***	8.566***	-0.146***	0.134***
	(0.001)	(0.000)	(<0.000)	(0.002)	(<0.000)	(0.000)	(0.001)	(<0.000)

C2 x R4	-0.539**	-51.68***	-0.164	23.49	-0.125	-0.964	-0.0788**	-0.0225*
	(0.002)	(0.001)	(0.620)	(0.382)	(0.735)	(0.588)	(0.001)	(0.044)
C3 x R4	-0.0481	-15.96	0.793	22.14	0.725**	4.670*	-0.0968	0.0552
	(0.762)	(0.184)	(0.351)	(0.659)	(0.003)	(0.012)	(0.325)	(0.261)
C4 x R4	-0.913***	-88.54***	1.885*	100.0*	1.253***	3.744	-0.0608***	0.0730***
	(<0.000)	(0.000)	(0.032)	(0.025)	(<0.000)	(0.060)	(<0.000)	(<0.000)
C5 x R4	-1.571***	-150.6***	1.590**	37.08	1.368	7.861**	-0.0894	0.103*
	(<0.000)	(0.000)	(0.003)	(0.280)	(0.068)	(0.009)	(0.395)	(0.027)
C6 x R4	-0.311***	-43.24***	1.032*	14.67	1.020***	5.874**	-0.0656	0.0356
	(<0.000)	(0.000)	(0.032)	(0.679)	(<0.000)	(0.002)	(0.443)	(0.111)
C7 x R4	0.540	40.53	1.633	55.54	1.976***	10.56***	-0.00429	0.0795**
	(0.068)	(0.068)	(0.095)	(0.257)	(<0.000)	(0.000)	(0.961)	(0.004)
C1 x R5	0.235	28.75	-1.359	-97.85	-0.965**	-1.102	-0.0712	-0.0398**
	(0.316)	(0.295)	(0.229)	(0.245)	(0.003)	(0.603)	(0.069)	(0.002)
C2 x R5	-0.332*	-34.69*	0.612	33.97	0.122	1.436	-0.370*	0.00285
	(0.014)	(0.011)	(0.495)	(0.593)	(0.600)	(0.482)	(0.023)	(0.831)
C3 x R5	0.239	25.67	-3.443***	-237.9**	-2.001***	-4.488*	-0.0666	-0.0650**
	(0.173)	(0.302)	(<0.000)	(0.006)	(<0.000)	(0.035)	(0.187)	(0.002)
C4 x R5	0.336***	36.43**	2.292	84.70	0.421	2.088	-0.126	0.0434*
	(<0.000)	(0.004)	(0.317)	(0.515)	(0.538)	(0.363)	(0.299)	(0.036)
C5 x R5	0.799**	86.37*	6.498***	379.9***	0.801	2.959	0.335***	0.236***
	(0.007)	(0.026)	(<0.000)	(0.000)	(0.352)	(0.395)	(<0.000)	(<0.000)
C6 x R5	-0.0652	-8.145	-0.822	-111.0	-0.807**	-2.040	-0.112	0.000508
	(0.613)	(0.684)	(0.627)	(0.308)	(0.006)	(0.354)	(0.321)	(0.983)
C7 x R5	0.971***	100.6***	5.708**	329.4***	1.118	6.150**	0.0342	0.125***
	(<0.000)	(0.000)	(0.002)	(0.000)	(0.071)	(0.008)	(0.699)	(<0.000)
C1 x R6	-0.0584	-8.046	-4.529***	-464.9***	-1.261***	-3.217**	0.231***	-0.0950***
	(0.409)	(0.391)	(<0.000)	(0.000)	(<0.000)	(0.009)	(<0.000)	(<0.000)
C2 x R6	-0.305**	-35.82**	-3.362***	-346.5***	-0.998***	-2.397*	0.121*	-0.0797***
	(0.004)	(0.006)	(<0.000)	(0.000)	(<0.000)	(0.048)	(0.045)	(<0.000)
C3 x R6	-0.405***	-40.61***	-2.887***	-285.4***	-1.359***	-3.980**	0.158**	-0.0724***
	(<0.000)	(0.000)	(<0.000)	(0.000)	(<0.000)	(0.001)	(0.003)	(<0.000)
C4 x R6	-0.675***	-79.48***	-1.168	-121.3	-0.284	-1.219	0.142***	-0.0481*
	(<0.000)	(0.000)	(0.227)	(0.246)	(0.340)	(0.359)	(<0.000)	(0.011)
C5 x R6	-1.281***	-143.6***	5.395**	578.9**	1.289***	3.476	-0.198***	0.0911
	(<0.000)	(0.000)	(0.004)	(0.003)	(<0.000)	(0.085)	(<0.000)	(0.051)
C6 x R6	-0.724***	-75.57***	-5.194***	-529.9***	-1.376***	-4.131**	0.224***	-0.128***
	(<0.000)	(0.000)	(<0.000)	(0.000)	(<0.000)	(0.002)	(<0.000)	(<0.000)
C7 x R6	-0.575***	-61.83***	-2.249**	-233.7**	-0.938***	-3.057*	0.289***	-0.0814***
	(<0.000)	(0.000)	(0.002)	(0.004)	(<0.000)	(0.024)	(<0.000)	(<0.000)
C1 x R7	-0.174***	-19.60***	-1.700	-297.0	-0.121	-0.492	0.0295	0.00217
	(<0.000)	(0.000)	(0.412)	(0.206)	(0.749)	(0.764)	(0.147)	(0.947)

C2 x R7	-0.00658	3.761	-4.774***	-490.1**	-1.539***	-4.998**	0.00337	-0.0898***
	(0.943)	(0.721)	(<0.000)	(0.001)	(<0.000)	(0.002)	(0.938)	(<0.000)
C3 x R7	-0.410***	-36.91**	1.522	112.2	-0.183	-0.977	-0.0622**	-0.00987
	(<0.000)	(0.003)	(0.378)	(0.549)	(0.493)	(0.556)	(0.004)	(0.682)
C4 x R7	-0.612***	-74.14***	0.809	20.98	0.338	1.072	0.0553	0.0150
	(<0.000)	(0.000)	(0.469)	(0.874)	(0.166)	(0.547)	(0.181)	(0.536)
C5 x R7	-0.679***	-68.93**	-4.169**	-473.7*	-0.719*	-2.351	-0.199**	-0.101***
	(0.001)	(0.007)	(0.009)	(0.019)	(0.025)	(0.384)	(0.004)	(<0.000)
C6 x R7	-0.485***	-39.70***	-4.789**	-535.0*	-1.076**	-4.067*	-0.0371	-0.0893**
	(<0.000)	(0.000)	(0.005)	(0.012)	(0.005)	(0.018)	(0.367)	(0.003)
C7 x R7	-0.223**	-16.03	-1.071	-184.8*	-0.463	-1.504	0.0922***	-0.0407
	(0.005)	(0.116)	(0.262)	(0.049)	(0.082)	(0.404)	(<0.000)	(0.064)
Constant	43.31***	1891.8***	30.48***	924.0***	0.216	-0.0886	-25.71***	-38.88***
	(<0.000)	(0.000)	(<0.000)	(0.000)	(0.319)	(0.956)	(<0.000)	(<0.000)
N	3,024	3,024	3,024	3,024	3,024	3,024	3,024	3,024
R Square	0.9815	0.9837	0.8781	0.7999	0.1988	0.1979		
Wald $\chi2$	154,585.67	176,151.92	20,968.34	11,637.73	722.38	718.14		
(d.f.=112)	(<0.000)	(<0.000)	(<0.000)	(<0.000)	(<0.000)	(<0.000)		
LR $\chi2$							55,119.10	19,636.25
(d.f.=112)							(<0.000)	(<0.000)

Note: 1) Dependent variables are annual mean temperature, amount of precipitation, PDSI (Palmer Drought Severity Index), hot days, and wet days. Independent variables are time trend, interactions of ENSO and regional dummies, interactions of DCV and regional dummies, regional dummies, and US state dummies.
2) All equations are random effects linear panel data models except log of hot days which is zero-inflated Poisson random effects model and log of wet days which is Poisson random effects model.
3) Regional Dummies are R1 for Central(IA, IL, IN, MI, MN, MO, OH, WI); R2 for Mountains(AZ, CO, ID, MT, NM, NV, UT, WY); R3 for Northeast(CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); R4 for Northern Plains(KS, ND, NE, SD); R5 for Pacific(CA, OR, WA); R6 for Southeast(AL, FL, GA, KY, NC, SC, TN, VA, WV); R7 for Southern Plains(AR, LA, MS, OK, TX).
4) DCV (PDO, TAG, WPWP) dummy variables identify 7 different DCV phase combinations. C1 for (PDO+,TAG-,WPWP-); C2 for (PDO-,TAG+,WPWP-); C3 for (PDO-,TAG-,WPWP+); C4 for (PDO+,TAG+,WPWP-); C5 for (PDO+,TAG-,WPWP+); C6 for (PDO-,TAG+,WPWP+); and C7 for (PDO+,TAG+,WPWP+); where C8 for (PDO-,TAG-,WPWP-) is excluded from co-linearity.
5) Estimated coefficients with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
6) The dummy coefficients of state and regions are not shown.

Table 4: Skew-normal regression on crop yields

	Corn	Cotton	Sorghum	Soybeans	Wheat
Trend	2.132***	-0.645	1.295***	0.152*	0.598***
	(<0.000)	(0.724)	(<0.000)	(0.014)	(<0.000)
Trend^2	-0.00324	0.139***	-0.00900***	0.00247**	-0.0000412
	(0.216)	(<0.000)	(<0.000)	(0.002)	(0.963)
Harvested Acreage	0.00191	-0.000309	0.00466***	0.000425	0.000472
	(0.107)	(0.965)	(<0.000)	(0.160)	(0.367)
Temperature	-2.355	196.8***	-6.326*	3.407***	-1.080
	(0.545)	(<0.000)	(0.041)	(<0.000)	(0.517)
Temperature^2	0.0295	-1.605***	0.0593*	-0.0304***	0.00913
	(0.462)	(<0.000)	(0.029)	(<0.000)	(0.592)
PDSI	1.494**	-7.155	0.776	0.652***	0.180
	(0.008)	(0.312)	(0.194)	(<0.000)	(0.470)
PDSI^2	-0.210*	-1.240	-0.0416	-0.0706*	-0.0509
	(0.050)	(0.352)	(0.633)	(0.026)	(0.248)
Precipitation	0.931**	-0.342	0.304	0.193**	0.226
	(0.004)	(0.884)	(0.111)	(0.006)	(0.068)
Precipitation^2	-0.0108***	0.0117	-0.00499**	-0.00234***	-0.00406**
	(<0.000)	(0.588)	(0.009)	(0.001)	(0.001)
Day Temp>90° F	-0.292***	-1.567***	-0.175***	-0.0856***	-0.0257
	(<0.000)	(<0.000)	(<0.000)	(<0.000)	(0.136)
Day Precip>1 inch	-0.0586	-0.317	0.0140	0.0289*	-0.0262
	(0.190)	(0.478)	(0.735)	(0.050)	(0.297)
El Niño x R1	4.154***	-16.70*	1.748	0.314*	-0.865*
	(<0.000)	(0.024)	(0.225)	(0.042)	(0.034)
El Niño x R2	-0.968	-22.41	-3.287***		0.591
	(0.236)	(0.488)	(<0.000)		(0.364)
El Niño x R3	0.0653		9.585***	-1.330***	-0.850*
	(0.930)		(<0.000)	(<0.000)	(0.022)
El Niño x R4	0.473	94.07***	-0.203	-0.0509	0.466
	(0.734)	(<0.000)	(0.797)	(0.824)	(0.291)

El Niño x R5	1.068	-2.178	-2.235***	-0.462	-2.388***
	(0.601)	(0.637)	(<0.000)	(0.107)	(<0.000)
El Niño x R6	1.949	-13.45	-1.067		-0.884**
	(0.190)	(0.243)	(0.186)		(0.001)
El Niño x R7	-0.910	17.85**	0.458	0.336	-0.206
	(0.481)	(0.002)	(0.492)	(0.254)	(0.520)
La Niña x R1	-1.597*	-49.90***	-4.343*	-0.595**	-0.926*
	(0.033)	(<0.000)	(0.012)	(0.009)	(0.021)
La Niña x R2	-3.092***	-24.79	-2.827***		1.143
	(<0.000)	(0.594)	(<0.000)		(0.061)
La Niña x R3	-1.743		2.555	-1.821***	-0.663
	(0.151)		(0.124)	(<0.000)	(0.310)
La Niña x R4	-2.552	55.75***	-3.006*	-1.961***	1.999
	(0.164)	(<0.000)	(0.010)	(<0.000)	(0.072)
La Niña x R5	-2.633	-88.25***	-3.744***	-1.598***	0.386
	(0.144)	(<0.000)	(<0.000)	(<0.000)	(0.791)
La Niña x R6	-0.852	-26.01***	-1.009		0.00384
	(0.503)	(<0.000)	(0.205)		(0.991)
La Niña x R7	-1.836	-0.896	-1.309**	-0.789**	0.597
	(0.452)	(0.804)	(0.007)	(0.009)	(0.315)
C1 x R1	-1.747	32.90	-0.845	1.626**	0.789
	(0.387)	(0.094)	(0.672)	(0.007)	(0.364)
C2 x R1	3.822	-30.67	-6.331**	-1.857**	-1.148
	(0.137)	(0.482)	(0.005)	(0.009)	(0.177)
C3 x R1	-4.981	-10.50	3.923	0.0507	2.545
	(0.094)	(0.646)	(0.105)	(0.958)	(0.079)
C4 x R1	-1.298	-19.16	-5.812	0.602	-1.111
	(0.451)	(0.178)	(0.079)	(0.203)	(0.152)
C5 x R1	-7.497*	4.030	-2.561	-2.790**	1.657
	(0.013)	(0.900)	(0.460)	(0.007)	(0.235)
C6 x R1	-2.146	83.95***	2.951	1.447*	1.162
	(0.526)	(<0.000)	(0.209)	(0.034)	(0.490)
C7 x R1	-7.736**	-102.4***	-4.309	2.022	2.601
	(0.007)	(<0.000)	(0.217)	(0.074)	(0.064)

C1 x R2	7.135*** (0.001)	83.98*** (<0.000)	-4.997 (0.106)		1.253 (0.381)
C2 x R2	-5.847 (0.078)	47.53 (0.060)	-1.076 (0.676)		-0.991 (0.530)
C3 x R2	17.15** (0.002)	4.990 (0.863)	-10.69* (0.016)		0.208 (0.947)
C4 x R2	0.758 (0.674)	37.89 (0.231)	-7.403** (0.010)		0.598 (0.557)
C5 x R2	19.12** (0.007)	-66.05 (0.152)	-15.67 (0.160)		0.459 (0.881)
C6 x R2	9.409 (0.055)	64.20* (0.027)	-3.404 (0.535)		1.351 (0.704)
C7 x R2	11.36** (0.007)	0.813 (0.976)	-14.88* (0.011)		3.645 (0.233)
C1 x R3	2.145 (0.053)			0.0729 (0.939)	-0.783 (0.343)
C2 x R3	9.716*** (<0.000)			-3.088*** (<0.000)	-0.387 (0.714)
C3 x R3	-6.991 (0.085)		-22.63*** (<0.000)	0.150 (0.819)	3.043 (0.099)
C4 x R3	4.020** (0.007)		-10.42** (0.004)	-1.839** (0.002)	-1.671* (0.012)
C5 x R3	-0.588 (0.921)		0.386 (0.934)	-1.687 (0.059)	-4.801*** (<0.000)
C6 x R3	-2.032 (0.367)		-28.44*** (<0.000)	1.142 (0.331)	1.617 (0.491)
C7 x R3	-11.26*** (<0.000)		-29.46*** (<0.000)	-1.528 (0.310)	4.049* (0.024)
C1 x R4	-1.489 (0.156)	151.8*** (<0.000)	2.036 (0.144)	0.292 (0.421)	-1.828*** (<0.000)
C2 x R4	-0.883 (0.900)		-0.329 (0.827)	-2.136** (0.004)	-1.116 (0.090)
C3 x R4	-1.916 (0.515)	82.33*** (<0.000)	3.375 (0.197)	-0.777 (0.395)	-5.160*** (<0.000)

C4 x R4	-0.934 (0.585)	-97.95*** (<0.000)	0.500 (0.685)	0.597 (0.363)	1.230 (0.060)
C5 x R4	-1.655 (0.502)	188.5*** (<0.000)	-2.137 (0.595)	0.462 (0.562)	-4.318* (0.025)
C6 x R4	-3.160 (0.604)	99.88*** (0.001)	6.544 (0.101)	0.625 (0.705)	-3.952** (0.002)
C7 x R4	-3.129 (0.107)	20.30 (0.282)	4.647* (0.033)	0.774 (0.283)	-4.670*** (<0.000)
C1 x R5	19.11** (0.002)	-100.1*** (<0.000)	2.553*** (<0.000)	-0.911* (0.032)	5.242** (0.001)
C2 x R5	-8.242* (0.012)	-190.3*** (<0.000)	-0.615 (0.532)	0.443 (0.500)	-6.593* (0.020)
C3 x R5	21.90*** (0.001)	-75.01*** (<0.000)	-2.803 (0.174)	-1.199 (0.057)	2.807 (0.357)
C4 x R5	6.165 (0.247)	-122.2*** (<0.000)	-4.248*** (<0.000)	-0.513 (0.128)	0.710 (0.489)
C5 x R5	14.84 (0.093)	-159.3*** (<0.000)	-5.182 (0.088)	-1.162 (0.286)	4.372 (0.102)
C6 x R5	20.25** (0.007)	-11.85 (0.560)	-1.178 (0.587)	0.244 (0.699)	1.489 (0.513)
C7 x R5	22.14* (0.012)	-170.5*** (<0.000)	1.031 (0.582)	-2.473*** (0.001)	6.179*** (<0.000)
C1 x R6	-2.242 (0.054)	8.954 (0.425)	-0.515 (0.792)		0.267 (0.687)
C2 x R6	8.062*** (<0.000)	-61.30** (0.004)	1.557 (0.258)		0.622 (0.499)
C3 x R6	-2.842 (0.257)	-61.82* (0.019)	-1.253 (0.613)		2.927 (0.055)
C4 x R6	1.763 (0.177)	-5.905 (0.695)	-2.551*** (0.001)		0.134 (0.848)
C5 x R6	-2.918 (0.430)	-25.09 (0.401)	0.617 (0.869)		0.122 (0.942)
C6 x R6	-0.766 (0.840)	-27.44 (0.225)	0.743 (0.765)		4.030** (0.003)

C7 x R6	-6.637**	-52.93*	-2.894		3.212*
	(0.007)	(0.013)	(0.239)		(0.031)
C1 x R7	3.343	20.16*	3.973*	-1.154	1.711*
	(0.588)	(0.028)	(0.038)	(0.092)	(0.028)
C2 x R7	-1.968	-31.58	0.155	0.946	4.068***
	(0.743)	(0.080)	(0.919)	(0.142)	(<0.000)
C3 x R7	5.668	-44.52	7.817	-3.606**	2.083
	(0.390)	(0.134)	(0.063)	(0.006)	(0.310)
C4 x R7	0.134	-10.90	-0.201	-0.345	4.572***
	(0.962)	(0.437)	(0.932)	(0.735)	(<0.000)
C5 x R7	7.601	-19.92	6.778	-1.572	-0.699
	(0.334)	(0.388)	(0.156)	(0.371)	(0.801)
C6 x R7	9.544	30.35	11.24**	0.858	0.868
	(0.312)	(0.102)	(0.010)	(0.669)	(0.661)
C7 x R7	4.918	-35.10*	5.529	-4.312**	1.899
	(0.216)	(0.027)	(0.137)	(0.001)	(0.244)
Constant	64.44	-5406.1***	208.1*	-73.62***	53.15
	(0.486)	(<0.000)	(0.018)	(<0.000)	(0.183)
Gamma	-0.652***	-0.102	-0.236	-0.453***	-0.499***
	(<0.000)	(0.442)	(0.190)	(<0.000)	(<0.000)
Ln(Sigma)	2.677***	4.657***	2.166***	1.308***	1.933***
	(<0.000)	(<0.000)	(<0.000)	(<0.000)	(<0.000)
N	2,634	1,094	1,313	1,885	2,624
Wald χ2 (d.f.)	27,943.94 (117)	6,333.82 (83)	6,781.22 (94)	10,379.14 (86)	16,862.48 (115)
	(<0.000)	(<0.000)	(<0.000)	(<0.000)	(<0.000)
Normality χ2 (d.f.)	172.33 (1)	1.27 (1)	5.75 (1)	42.53 (1)	68.26 (1)
	(<0.000)	0.2607	0.0165	(<0.000)	(<0.000)

Note: 1) Dependent variables are yearly average crop yield per harvested acre by state. Independent variables are crop acreage, time trend, mean temperature, amount of precipitation, PDSI (Palmer Drought Severity Index), hot days, interactions of ENSO and regional dummies, interactions of DCV and regional dummies, regional dummies, and US state dummies

2) Regional Dummies. R1=Central(IA, IL, IN, MI, MN, MO, OH, WI); R2=Mountains(AZ, CO, ID, MT, NM, NV, UT, WY); R3=Northeast(CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); R4=Northern Plains(KS, ND, NE, SD); R5=Pacific(CA, OR, WA); R6=Southeast(AL, FL, GA, KY, NC, SC, TN, VA, WV); R7=Southern Plains(AR, LA, MS, OK, TX).

3) DCV dummy variables cover 7 different DCV phase combinations. C1=(PDO+,TAG-,WPWP-); C2=(PDO-,TAG+,WPWP-); C3=(PDO-,TAG-,WPWP+); C4=(PDO+,TAG-,WPWP+); C5=(PDO+,TAG+,WPWP-); C6=(PDO-,TAG+,WPWP+); and C7=(PDO+,TAG+,WPWP+); where C8=(PDO-,TAG-,WPWP-)is excluded and is in the intercept.

4) Estimated coefficients with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

5) The dummy variable coefficients for regions and states are not shown.

Table 5: Total DCV impacts on crop yields by region

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN							
Central	0.265	-0.911***	0.107	0.408**	-7.375*	0.257	-6.539*
	(0.598)	(<0.001)	(0.651)	(0.002)	(0.015)	(0.197)	(0.02)
Mountains	7.136**	-0.868**	15.647**	0.521*	20.157**	0.646	14.343**
	(0.001)	(0.004)	(0.003)	(0.018)	(0.006)	(0.061)	(0.002)
Northeast	1.841*	9.716***	-0.081***	4.02**	0.945		-11.348***
	(0.021)	(<0.001)	(<0.001)	(0.007)	(0.285)		(<0.001)
Northern Plains	2.825***	0.024***	0.183	1.755***	3.934***	1.645**	0.807
	(<0.001)	(<0.001)	(0.517)	(<0.001)	(<0.001)	(0.002)	(0.201)
Pacific	17.696**	-8.437*	19.27**		1.802	19.572**	23.87**
	(0.004)	(0.01)	(0.003)		(0.082)	(0.009)	(0.006)
Southeast	-0.447	7.604***	-0.794*	-0.041***	0.053	-0.315	-6.993**
	(0.219)	(<0.001)	(0.019)	(<0.001)	(0.908)	(0.397)	(0.005)
Southern Plains	1.56***	-0.482	0.198	0.769***	0.77*	0.628	0.652*
	(<0.001)	(0.273)	(0.315)	(<0.001)	(0.023)	(0.111)	(0.015)
COTTON							
Central	0.269***	0.348***	7.206***	-12.955***	-8.256	91.727***	-102.413***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.082)	(<0.001)	(<0.001)
Mountains	95.485***		18.495***	8.446***	28.623**	86.495**	25.346***
	(<0.001)		(<0.001)	(<0.001)	(0.001)	(0.003)	(<0.001)
Northeast							
Northern Plains	122.638***		69.359**	-135.774***	166.512***	98.564**	-20.289**
	(<0.001)		(0.001)	(<0.001)	(<0.001)	(0.001)	(0.001)
Pacific	-91.672***	-190.816***	-65.581***	-118.204***	-147.974***		-161.651***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)

Southeast	-0.381***	-61.209**	-61.353*	-0.554	0.89	0.792	-53.755*
	(<0.001)	(0.004)	(0.022)	(0.806)	(0.838)	(0.786)	(0.014)
Southern Plains	19.868*	-5.921***	-4.346**	-0.395	-3.159	-6.879**	-39.706*
	(0.03)	(<0.001)	(0.007)	(0.862)	(0.198)	(0.003)	(0.012)
SORGHUM							
Central	-1.809**	-6.331**	-2.366*	-0.926	-0.522	-1.395**	-1.234**
	(0.009)	(0.005)	(0.01)	(0.105)	(0.298)	(0.004)	(0.009)
Mountains	-0.181		-14.278**	-8.813**	-0.213	-2.515*	-15.288*
	(0.116)		(0.005)	(0.003)	(0.776)	(0.039)	(0.01)
Northeast			-22.641***	-10.015***	-5.771	-32.051***	-31.512***
			(<0.001)	(<0.001)	(0.251)	(<0.001)	(<0.001)
Northern Plains	-0.99	-0.678	-1.295**	-0.49	-0.64	-1.716**	3.968
	(0.057)	(0.09)	(0.002)	(0.49)	(0.432)	(0.003)	(0.075)
Pacific	3.259***	-1.059**	0.497	-5.759***	0.037	-0.548	-2.114*
	(<0.001)	(0.009)	(0.2)	(<0.001)	(0.927)	(0.073)	(0.024)
Southeast	2.969*	1.521**	1.85**	-1.798*	-2.989*	2.721**	1.13*
	(0.01)	(0.009)	(0.007)	(0.047)	(0.015)	(0.008)	(0.011)
Southern Plains	5.302*	2.092**	-0.867	-0.821*	1.76**	13.399**	0.881**
	(0.011)	(0.005)	(0.066)	(0.025)	(0.004)	(0.004)	(0.001)
SOYBEANS							
Central	1.898**	-1.692*	-0.007	0.037	-3.029**	1.47*	0.951***
	(0.002)	(0.016)	(0.907)	(0.423)	(0.003)	(0.031)	(<0.001)
Mountains							
Northeast	-0.395***	-3.083***	-0.028***	-1.856**	0.6**		0.069
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.009)		(0.199)
Northern Plains	0.956***	-2.323**	0.942***	0.282*	-0.375*	0.866***	0.559***
	(<0.001)	(0.002)	(<0.001)	(0.028)	(0.013)	(<0.001)	(<0.001)
Pacific	-1.296**	-0.228*	-0.647***	0.161**	0.547***	-0.476**	-2.843***
	(0.003)	(0.034)	(<0.001)	(0.008)	(<0.001)	(0.001)	(<0.001)
Southeast							

Southern Plains	0.009	-0.411**	-3.828**	0.418***	-0.129	-0.416**	-4.512**
	(0.481)	(0.001)	(0.004)	(<0.001)	(0.234)	(0.001)	(0.001)
WHEAT							
Central	-0.898**		-0.736**			-0.468**	-0.497**
	(0.001)		(0.001)			(0.001)	(0.001)
Mountains			0.288**	-0.169**			
			(0.001)	(0.001)			
Northeast	1.187**	0.956**		-1.065	-9.433***		4.831**
	(0.001)	(0.001)		(0.116)	(<0.001)		(0.008)
Northern Plains	-2.548***		-5.161***	-0.426**	-4.319*	-3.953**	-4.67***
	(<0.001)		(<0.001)	(0.001)	(0.025)	(0.002)	(<0.001)
Pacific	5.243**	-6.593*	0.877**		-1.648**		4.779***
	(0.001)	(0.02)	(0.001)		(0.001)		(<0.001)
Southeast	1.952**	1.266**	1.07**	0.644**	-2.475**	6.046***	4.136**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(<0.001)	(0.007)
Southern Plains	2.902***	5.929***	-0.537**	4.471***	1.834**	2.032**	0.694**
	(<0.001)	(<0.001)	(0.001)	(<0.001)	(0.001)	(0.001)	(0.001)

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 6: Direct and indirect DCV impacts on crop yields by region

		(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN								
(bushels/acre)								
Central	Direct					-7.498*		-7.736**
						(0.013)		(0.007)
	Indirect	0.265	-0.911***	0.107	0.408**	0.123***	0.257	1.198***
		(0.598)	(<0.001)	(0.651)	(0.002)	(<0.001)	(0.197)	(<0.001)
Mountains	Direct	7.136**		17.155**		19.121**		11.357**
		(0.001)		(0.002)		(0.007)		(0.007)
	Indirect		-0.868**	-1.509**	0.521*	1.037	0.646	2.986***
			(0.004)	(0.001)	(0.018)	(0.066)	(0.061)	(<0.001)
Northeast	Direct		9.716***		4.02**			-11.26***
			(<0.001)		(0.007)			(<0.001)
	Indirect	1.841*		-0.081***		0.945		-0.089***
		(0.021)		(<0.001)		(0.285)		(<0.001)
Northern Plains	Direct							
	Indirect	2.825***	0.024***	0.183	1.755***	3.934***	1.645**	0.807
		(<0.001)	(<0.001)	(0.517)	(<0.001)	(<0.001)	(0.002)	(0.201)
Pacific	Direct	19.111**	-8.242*	21.902**			20.252**	22.141*
		(0.002)	(0.012)	(0.001)			(0.007)	(0.012)
	Indirect	-1.416**	-0.195	-2.633***		1.802	-0.68**	1.73
		(0.008)	(0.209)	(<0.001)		(0.082)	(0.008)	(0.059)

Southeast	Direct		8.063***					-6.637**
			(<0.001)					(0.007)
	Indirect	-0.447	-0.46	-0.794*	-0.041***	0.053	-0.315	-0.356
		(0.219)	(0.129)	(0.019)	(<0.001)	(0.908)	(0.397)	(0.111)
Southern Plains	Direct							
	Indirect	1.56***	-0.482	0.198	0.769***	0.77*	0.628	0.652*
		(<0.001)	(0.273)	(0.315)	(<0.001)	(0.023)	(0.111)	(0.015)
COTTON								
(lbs/acre)								
Central	Direct						83.955***	-102.413***
							(<0.001)	(<0.001)
	Indirect	0.269***	0.348***	7.206***	-12.955***	-8.256	7.773***	
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.082)	(<0.001)	
Mountains	Direct	83.982***					64.202*	
		(<0.001)					(0.027)	
	Indirect	11.503***		18.495***	8.446***	28.623**	22.294***	25.346***
		(<0.001)		(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)
Northeast	Direct							
	Indirect							
Northern Plains	Direct	151.758***		82.331***	-97.955***	188.543***	99.879**	
		(<0.001)		(<0.001)	(<0.001)	(<0.001)	(0.001)	
	Indirect	-29.121***		-12.972*	-37.819***	-22.031**	-1.316	-20.289**
		(<0.001)		(0.012)	(<0.001)	(0.003)	(0.786)	(0.001)

Pacific	Direct	-100.091***	-190.304***	-75.007***	-122.235***	-159.259***		-170.519***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)
	Indirect	8.419*	-0.513	9.426***	4.031*	11.286*		8.869*
		(0.02)	(0.69)	(<0.001)	(0.014)	(0.02)		(0.013)
Southeast	Direct		-61.303**	-61.82*				-52.931*
			(0.004)	(0.019)				(0.013)
	Indirect	-0.381***	0.094	0.467	-0.554	0.89	0.792	-0.825
		(<0.001)	(0.952)	(0.743)	(0.806)	(0.838)	(0.786)	(0.662)
Southern Plains	Direct	20.163*						-35.103*
		(0.028)						(0.027)
	Indirect	-0.296	-5.921***	-4.346**	-0.395	-3.159	-6.879**	-4.603***
		(0.553)	(<0.001)	(0.007)	(0.862)	(0.198)	(0.003)	(<0.001)
SORGHUM								
(bushels/acre)								
Central	Direct		-6.331**					
			(0.005)					
	Indirect	-1.809**		-2.366*	-0.926	-0.522	-1.395**	-1.234**
		(0.009)		(0.01)	(0.105)	(0.298)	(0.004)	(0.009)
Mountains	Direct			-10.688*	-7.404*			-14.883*
				(0.016)	(0.01)			(0.011)
	Indirect	-0.181		-3.59*	-1.41**	-0.213	-2.515*	-0.406
		(0.116)		(0.041)	(0.005)	(0.776)	(0.039)	(0.389)
Northeast	Direct			-22.632***	-10.417**		-28.44***	-29.463***
				(<0.001)	(0.004)		(<0.001)	(<0.001)
	Indirect			-0.01	0.403	-5.771	-3.611	-2.05
				(0.997)	(0.903)	(0.251)	(0.329)	(0.438)

Northern Plains	Direct							4.648*
								(0.033)
	Indirect	-0.99	-0.678	-1.295**	-0.49	-0.64	-1.716**	-0.68**
		(0.057)	(0.09)	(0.002)	(0.49)	(0.432)	(0.003)	(0.009)
Pacific	Direct	2.554***			-4.248***			
		(<0.001)			(<0.001)			
	Indirect	0.706	-1.059**	0.497	-1.511*	0.037	-0.548	-2.114*
		(0.158)	(0.009)	(0.2)	(0.011)	(0.927)	(0.073)	(0.024)
Southeast	Direct				-2.551**			
					(0.001)			
	Indirect	2.969*	1.521**	1.85**	0.754*	-2.989*	2.721**	1.13*
		(0.01)	(0.009)	(0.007)	(0.026)	(0.015)	(0.008)	(0.011)
Southern Plains	Direct	3.973*					11.241*	
		(0.038)					(0.01)	
	Indirect	1.329**	2.092**	-0.867	-0.821*	1.76**	2.158**	0.881**
		(0.009)	(0.005)	(0.066)	(0.025)	(0.004)	(0.002)	(0.001)
SOYBEANS								
(bushels/acre)								
Central	Direct	1.626**	-1.858**			-2.791**	1.448*	
		(0.007)	(0.009)			(0.007)	(0.034)	
	Indirect	0.272*	0.166	-0.007	0.037	-0.238**	0.022	0.951***
		(0.033)	(0.186)	(0.907)	(0.423)	(0.003)	(0.57)	(<0.001)
Mountains	Direct							
	Indirect							

Northeast	Direct		-3.089***		-1.839**			
			(<0.001)		(0.002)			
	Indirect	-0.395***	0.006	-0.028***	-0.017	0.6**		0.069
		(<0.001)	(0.94)	(<0.001)	(0.771)	(0.009)		(0.199)
Northern Plains	Direct		-2.136**					
			(0.004)					
	Indirect	0.956***	-0.188***	0.942***	0.282*	-0.375*	0.866***	0.559***
		(<0.001)	(<0.001)	(<0.001)	(0.028)	(0.013)	(<0.001)	(<0.001)
Pacific	Direct	-0.911*						-2.474**
		(0.032)						(0.001)
	Indirect	-0.385**	-0.228*	-0.647***	0.161**	0.547***	-0.476**	-0.37***
		(0.001)	(0.034)	(<0.001)	(0.008)	(<0.001)	(0.001)	(<0.001)
Southeast	Direct							
	Indirect							
Southern Plains	Direct			-3.606**				-4.312**
				(0.006)				(0.001)
	Indirect	0.009	-0.411**	-0.222***	0.418***	-0.129	-0.416**	-0.2**
		(0.481)	(0.001)	(<0.001)	(<0.001)	(0.234)	(0.001)	(0.002)
WHEAT (bushels/acre)								
Central	Direct							
	Indirect	-0.898**		-0.736**			-0.468**	-0.497**
		(0.001)		(0.001)			(0.001)	(0.001)

Mountains	Direct							
	Indirect			0.288**	-0.169**			
				(0.001)	(0.001)			
Northeast	Direct				-1.672*	-4.802***		4.05*
					(0.012)	(<0.001)		(0.024)
	Indirect	1.187**	0.956**		0.608**	-4.631**		0.782**
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Northern Plains	Direct	-1.828***		-5.161***		-4.319*	-3.953**	-4.67***
		(<0.001)		(<0.001)		(0.025)	(0.002)	(<0.001)
	Indirect	-0.72**			-0.426**			
		(0.001)			(0.001)			
Pacific	Direct	5.243**	-6.593*					6.179***
		(0.001)	(0.02)					(<0.001)
	Indirect			0.877**		-1.648**		-1.4**
				(0.001)		(0.001)		(0.001)
Southeast	Direct						4.031**	3.213*
							(0.003)	(0.031)
	Indirect	1.952**	1.266**	1.07**	0.644**	-2.475**	2.015**	0.923**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Southern Plains	Direct	1.712*	4.069***		4.573***			
		(0.028)	(<0.001)		(<0.001)			
	Indirect	1.191**	1.86**	-0.537**	-0.102**	1.834**	2.032**	0.694**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: 1) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
2) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 7: Regional predicted mean crop yields by DCV phase combination

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO-, TAG-, WPWP-)
CORN								
Central	176.04	174.71	175.87	176.19	168.37	176.03	169.17	175.76
Mountains	181.60	173.33	190.28	174.82	194.45	174.94	188.77	174.27
Northeast	163.97	172.29	161.92	166.12	162.98	162.02	150.59	162.03
Northern Plains	157.84	154.90	155.10	156.68	158.82	156.61	155.70	154.87
Pacific	214.12	187.22	215.67	196.07	197.89	215.94	220.18	196.07
Southeast	145.68	154.10	145.29	146.11	146.21	145.80	139.08	146.15
Southern Plains	154.95	152.81	153.51	154.10	154.07	153.95	153.97	153.30
COTTON								
Central	979.01	979.13	986.07	965.5	970.36	1071.51	875.98	978.73
Mountains	1,349.60	1,259.27	1,270.98	1,268.06	1,287.95	1,340.50	1,277.77	1,259.27
Northeast								
Northern Plains	776.39	650.90	722.87	513.70	817.72	751.86	629.99	650.93
Pacific	1,506.33	1,400.73	1,532.04	1,480.02	1,452.94	1,600.97	1,437.32	1,600.96
Southeast	969.60	905.95	907.23	969.43	970.90	970.84	915.78	969.99
Southern Plains	973.08	946.32	948.10	952.20	949.45	945.37	912.49	952.62
SORGHUM								
Central	92.75	88.05	92.07	93.67	94.18	93.18	93.33	94.66
Mountains	78.63	78.85	64.14	69.83	78.57	76.28	63.33	78.85
Northeast								
Northern Plains	75.75	75.97	75.46	76.32	76.21	75.05	80.82	76.84
Pacific	103.00	98.41	100.11	93.52	99.58	98.99	97.29	99.65
Southeast	69.10	67.47	67.81	63.93	62.69	68.7	66.99	65.75
Southern Plains	72.97	71.28	69.04	68.43	68.81	80.39	69.16	69.01
SOYBEANS								
Central	49.04	45.31	47.09	47.13	44.05	48.59	48.07	47.09
Mountains								
Northeast	43.88	41.08	44.26	42.41	44.90	44.29	44.37	44.30
Northern Plains	42.24	38.80	42.26	41.54	40.86	42.16	41.81	41.24
Pacific	39.63	40.73	40.28	41.15	41.52	40.47	38.09	40.97
Southeast								
Southern Plains	40.93	40.46	36.97	41.35	40.79	40.48	36.36	40.92

WHEAT								
Central	67.15	68.10	67.32	68.10	68.10	67.61	67.59	68.10
Mountains	71.76	71.76	72.05	71.58	71.76	71.76	71.76	71.77
Northeast	67.81	67.60	66.56	65.48	57.10	66.56	71.45	66.56
Northern Plains	54.34	56.97	51.68	56.53	52.65	52.94	52.26	56.97
Pacific	83.60	71.32	78.96	78.06	76.41	78.06	82.86	78.06
Southeast	60.63	59.95	59.70	59.24	56.09	64.76	62.76	58.57
Southern Plains	55.78	59.00	52.19	57.32	54.61	54.87	53.48	52.76

Note: Yields of all crops are in bushels/acre, except for cotton yield which is in lbs/acre. The estimations take into account the presence of regional direct and indirect DCV effects.

Table 8: Generalized-least square regression on yield variance ($\hat{u}^2$)

	Corn	Cotton	Sorghum	Soybeans	Wheat
Trend	-4.027	221.2	-1.518	-0.316	-5.032***
	(0.390)	(0.280)	(0.323)	(0.273)	(0.000)
Trend$^{\wedge 2}$	0.0632	-0.0631	0.0630**	0.0104*	0.0845***
	(0.357)	(0.983)	(0.006)	(0.012)	(0.000)
Harvested Acreage	-0.0192	0.0171	0.0228	0.000910	-0.00786
	(0.574)	(0.992)	(0.058)	(0.493)	(0.196)
Temperature	63.70	-5730.2	54.59	-10.81*	40.88*
	(0.436)	(0.499)	(0.151)	(0.033)	(0.017)
Temperature$^{\wedge 2}$	-0.666	48.29	-0.559	0.0906	-0.477**
	(0.375)	(0.495)	(0.088)	(0.066)	(0.005)
PDSI	-66.58**	609.3	-2.419	-0.935	-1.362
	(0.008)	(0.595)	(0.757)	(0.531)	(0.770)
PDSI$^{\wedge 2}$	16.51**	-110.6	0.702	-0.00734	-0.959
	(0.004)	(0.690)	(0.678)	(0.982)	(0.358)
Precipitation	-3.115	527.8	-2.768	-1.276	-2.872
	(0.821)	(0.344)	(0.497)	(0.115)	(0.268)
Precipitation$^{\wedge 2}$	-0.00175	-4.376	0.0171	0.00823	0.0414
	(0.989)	(0.368)	(0.642)	(0.273)	(0.094)
Day Temp>90°	0.800	26.53	0.313	0.0814	0.207
	(0.556)	(0.569)	(0.414)	(0.273)	(0.419)
Day Precip>90	0.958	-61.16	0.407	0.307*	-0.266
	(0.692)	(0.552)	(0.614)	(0.026)	(0.563)
El Niño x R1	-184.5	1279.0	-24.43	-4.319	-3.217
	(0.051)	(0.832)	(0.486)	(0.342)	(0.855)
El Niño x R2	-42.88	2472.5	-25.20		26.66
	(0.669)	(0.587)	(0.480)		(0.131)
El Niño x R3	52.39		-311.9	1.245	-23.90
	(0.629)		(0.116)	(0.833)	(0.282)
El Niño x R4	-205.9	6068.1	19.02	-1.857	0.669
	(0.120)	(0.575)	(0.586)	(0.772)	(0.979)

El Niño x R5	145.3	-8029.0	-1.712	0.385	36.71
	(0.342)	(0.288)	(0.980)	(0.931)	(0.201)
El Niño x R6	-119.8	5732.0*	10.47		-10.03
	(0.176)	(0.028)	(0.672)		(0.554)
El Niño x R7	-114.4	288.3	6.430	-7.123	5.333
	(0.335)	(0.929)	(0.812)	(0.219)	(0.813)
La Niña x R1	-182.6	448.9	14.48	1.389	9.144
	(0.067)	(0.944)	(0.698)	(0.773)	(0.624)
La Niña x R2	-12.30	2811.9	-19.00		6.475
	(0.908)	(0.564)	(0.612)		(0.728)
La Niña x R3	113.4		-403.4*	6.914	-19.39
	(0.320)		(0.042)	(0.267)	(0.408)
La Niña x R4	-175.8	5173.3	-2.748	-0.923	9.859
	(0.209)	(0.639)	(0.940)	(0.892)	(0.708)
La Niña x R5	-3.198	-10643.8	-3.260	7.872	3.275
	(0.984)	(0.198)	(0.964)	(0.095)	(0.914)
La Niña x R6	-83.77	5666.4*	14.66		3.005
	(0.370)	(0.040)	(0.575)		(0.867)
La Niña x R7	-175.2	-855.3	-7.588	-11.87	-11.42
	(0.161)	(0.803)	(0.790)	(0.052)	(0.631)
C1 x R1	-170.8	-4267.6	-98.91	7.300	10.25
	(0.254)	(0.647)	(0.060)	(0.315)	(0.715)
C2 x R1	-352.6*	6990.5	-70.25	-6.943	-66.80*
	(0.018)	(0.410)	(0.166)	(0.344)	(0.016)
C3 x R1	-130.0	-5865.7	-147.2*	-8.081	-20.99
	(0.394)	(0.561)	(0.010)	(0.285)	(0.464)
C4 x R1	-367.6*	1076.3	-64.56	-4.871	-32.20
	(0.023)	(0.914)	(0.241)	(0.535)	(0.290)
C5 x R1	-257.1	-16241.0	-213.2*	3.241	122.4**
	(0.298)	(0.354)	(0.041)	(0.790)	(0.008)
C6 x R1	29.82	-8336.9	-111.6	-17.47*	-67.60*
	(0.852)	(0.393)	(0.053)	(0.027)	(0.025)
C7 x R1	-167.4	-4474.0	-144.8*	-11.57	-13.56
	(0.312)	(0.692)	(0.017)	(0.156)	(0.663)
C1 x R2	-308.6	-6849.0	-46.22		18.93
	(0.053)	(0.357)	(0.422)		(0.500)

C2 x R2	-411.4**	10292.9	-11.35		134.4***
	(0.009)	(0.137)	(0.837)		(0.000)
C3 x R2	-459.6**	-11188.7	-50.20		8.199
	(0.005)	(0.145)	(0.387)		(0.775)
C4 x R2	-582.9***	1730.8	-75.75		49.15
	(0.001)	(0.821)	(0.222)		(0.106)
C5 x R2	-587.8*	-19023.9	52.79		-6.658
	(0.026)	(0.140)	(0.591)		(0.886)
C6 x R2	-367.6*	-15147.4	54.39		34.92
	(0.031)	(0.059)	(0.365)		(0.245)
C7 x R2	-810.8***	-7382.3	-35.05		25.19
	(0.000)	(0.376)	(0.592)		(0.422)
C1 x R3	178.9			-2.629	-7.718
	(0.316)			(0.781)	(0.827)
C2 x R3	2.364			-3.989	-39.71
	(0.989)			(0.663)	(0.252)
C3 x R3	672.7***		352.6*	8.648	1.318
	(0.000)		(0.013)	(0.363)	(0.971)
C4 x R3	85.28		-49.22	-3.981	-15.45
	(0.651)		(0.730)	(0.695)	(0.688)
C5 x R3	409.1		-252.3	-20.75	-13.90
	(0.184)		(0.189)	(0.192)	(0.814)
C6 x R3	365.6		248.2	5.083	-27.49
	(0.060)		(0.257)	(0.604)	(0.460)
C7 x R3	60.05		45.51	-3.942	24.20
	(0.768)		(0.869)	(0.709)	(0.534)
C1 x R4	114.9	2971.9	-3.397	22.00*	-7.368
	(0.587)	(0.899)	(0.951)	(0.032)	(0.853)
C2 x R4	-40.61		22.15	2.373	-55.40
	(0.843)		(0.686)	(0.812)	(0.150)
C3 x R4	-127.0	11556.1	-45.20	-7.447	-2.459
	(0.554)	(0.623)	(0.425)	(0.478)	(0.951)
C4 x R4	-67.91	2745.3	-19.03	6.844	3.837
	(0.767)	(0.918)	(0.753)	(0.537)	(0.929)
C5 x R4	-219.0	3222.7	-36.78	7.487	-17.14
	(0.529)	(0.909)	(0.688)	(0.658)	(0.793)

C6 x R4	169.4	14433.3	-68.69	13.68	-14.84
	(0.451)	(0.554)	(0.247)	(0.214)	(0.723)
C7 x R4	18.01	2950.4	10.42	1.270	30.69
	(0.939)	(0.903)	(0.867)	(0.911)	(0.484)
C1 x R5	179.8	-1542.8	11.35	-0.803	74.77
	(0.460)	(0.908)	(0.915)	(0.912)	(0.102)
C2 x R5	-316.5	24980.7	50.78	1.864	47.09
	(0.179)	(0.052)	(0.606)	(0.798)	(0.287)
C3 x R5	-152.6	-5031.4	-9.547	3.894	52.20
	(0.535)	(0.704)	(0.931)	(0.603)	(0.258)
C4 x R5	5.698	17530.8	33.50	8.507	60.55
	(0.983)	(0.206)	(0.770)	(0.281)	(0.222)
C5 x R5	-220.7	-18009.7	-79.91	-3.983	53.25
	(0.583)	(0.366)	(0.701)	(0.737)	(0.480)
C6 x R5	49.97	-1860.9	-43.06	-1.987	-54.19
	(0.844)	(0.895)	(0.707)	(0.803)	(0.255)
C7 x R5	-66.83	-134.8	51.73	-2.229	-2.524
	(0.804)	(0.992)	(0.703)	(0.784)	(0.960)
C1 x R6	103.2	4121.2	65.47		-19.72
	(0.466)	(0.322)	(0.082)		(0.462)
C2 x R6	-135.5	1245.9	19.01		-77.67**
	(0.338)	(0.768)	(0.618)		(0.004)
C3 x R6	233.6	-1083.0	34.79		-40.68
	(0.108)	(0.806)	(0.382)		(0.135)
C4 x R6	-49.93	250.0	8.282		-60.04*
	(0.745)	(0.956)	(0.837)		(0.042)
C5 x R6	-46.49	-6408.7	62.60		-70.65
	(0.843)	(0.370)	(0.320)		(0.109)
C6 x R6	427.0**	-5204.7	23.69		-20.82
	(0.005)	(0.274)	(0.584)		(0.470)
C7 x R6	124.3	-11069.6*	56.41		-19.28
	(0.430)	(0.021)	(0.184)		(0.519)
C1 x R7	-61.66	-2833.7	-41.13	7.751	-20.10
	(0.744)	(0.588)	(0.340)	(0.397)	(0.572)
C2 x R7	-165.2	4737.2	-10.21	-3.894	-70.19*
	(0.373)	(0.372)	(0.812)	(0.669)	(0.046)

C3 x R7	-34.54	-317.6	-4.651	-5.504	-11.06
	(0.857)	(0.953)	(0.917)	(0.556)	(0.758)
C4 x R7	-66.46	2342.5	-35.36	-5.336	-43.26
	(0.746)	(0.677)	(0.449)	(0.591)	(0.263)
C5 x R7	-268.2	-5707.4	-38.47	-20.91	-25.03
	(0.388)	(0.503)	(0.590)	(0.168)	(0.669)
C6 x R7	315.0	-4516.5	33.45	13.66	-11.16
	(0.114)	(0.435)	(0.476)	(0.163)	(0.766)
C7 x R7	-146.2	-5023.1	-28.30	-8.890	-5.479
	(0.481)	(0.382)	(0.556)	(0.379)	(0.888)
Constant	-699.4	165965.3	-1091.1	355.5^{**}	-661.1
	(0.748)	(0.514)	(0.326)	(0.007)	(0.131)
N	2,634	1,094	1,313	1,885	2,624
Wald $\chi 2$ (d.f.)	640.70 (116)	103.54 (83)	176.69 (91)	196.18 (86)	738.85 (115)
	(<0.000)	(0.0631)	(<0.000)	(<0.000)	(<0.000)

Note: 1) Dependent variable = yearly average crop yield by state. Independent variables=crop acreage, time trend, mean temperature, amount of precipitation, PDSI (Palmer Drought Severity Index), hot days, interactions of ENSO and regional dummies, interactions of DCV and regional dummies, regional dummies, and US state dummies
2) Regional Dummies. R1=Central(IA, IL, IN, MI, MN, MO, OH, WI); R2=Mountains(AZ, CO, ID, MT, NM, NV, UT, WY); R3=Northeast(CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); R4=Northern Plains(KS, ND, NE, SD); R5=Pacific(CA, OR, WA); R6=Southeast(AL, FL, GA, KY, NC, SC, TN, VA, WV); R7=Southern Plains(AR, LA, MS, OK, TX).
3) DCV dummy variables for different DCV phase combinations. C1=(PDO+,TAG-,WPWP-); C2=(PDO-,TAG+,WPWP-); C3=(PDO-,TAG-,WPWP+); C4=(PDO+,TAG-,WPWP+); C5=(PDO+,TAG+,WPWP-); C6=(PDO-,TAG+,WPWP+); and C7=(PDO+,TAG+,WPWP+); where C8=(PDO-,TAG-,WPWP-)is excluded and is in the intercept.
4) Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
5) The dummy coefficients of regions and states are not shown.

Table 9: Total DCV impacts on crop variance by region

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN							
Central	23.813**	-346.39*		-383.595*			-37.001**
	(0.004)	(0.021)		(0.018)			(0.008)
Mountains		-411.44**	-473.363**	-582.853**	-675.046*	-420.81*	-883.365***
		(0.009)	(0.004)	(0.001)	(0.011)	(0.014)	(<0.001)
Northeast			672.736***				
			(<0.001)				
Northern Plains			28.073		-98.799**		
			(0.071)		(0.008)		
Pacific	63.062**	23.794**	58.412			19.611	
	(0.008)	(0.004)	(0.055)			(0.062)	
Southeast	30.639	28.88	24.049				
	(0.099)	(0.071)	(0.176)				
Southern Plains			-4.694*				
			(0.02)				
COTTON							
Central							
Mountains							
Northeast							
Northern Plains							
Pacific							-11069.57*
							(0.021)
Southeast							
Southern Plains							
SORGHUM							
Central			-145.436**		-210.794*	-110.876*	-143.377*
			(0.009)		(0.037)	(0.047)	(0.015)
Mountains							

Northeast							
Northern Plains							
Pacific							
Southeast							
Southern Plains							
SOYBEANS							
Central	-3.348*	-0.027*		6.715*	15.004*	-17.47*	-5.659*
	(0.033)	(0.026)		(0.033)	(0.033)	(0.027)	(0.033)
Mountains		4.064*		8.302*	15.084*		
		(0.033)		(0.033)	(0.032)		
Northeast	24.89*	6.166*		10.009*	17.852*	4.518*	0.026*
	(0.016)	(0.033)		(0.032)	(0.032)	(0.033)	(0.026)
Northern Plains	-0.032*	3.575*	5.626*	7.282*	14.863*	9.073*	6.612*
	(0.026)	(0.034)	(0.034)	(0.033)	(0.033)	(0.034)	(0.033)
Pacific	1.962*	-0.027*	5.19*	6.725*	8.178*	6.401*	2.941*
	(0.033)	(0.026)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)
Southeast							
Southern Plains							
WHEAT							
Central		-66.8*		5.294**	133.915**	-67.604*	
		(0.016)		(0.006)	(0.004)	(0.025)	
Mountains		134.363***			-6.716*	12.812*	
		(<0.001)			(0.041)	(0.017)	
Northeast		6.137***		7.707**	13.858**		-1.796
		(<0.001)		(0.004)	(0.002)		(0.067)
Northern Plains	1.793*	2.841		4.973		8.701**	
	(0.026)	(0.055)		(0.077)		(0.001)	
Pacific		3.191**		-3.58**	-7.966**		-7.897**
		(0.001)		(0.002)	(0.002)		(0.009)
Southeast		-72.711**	3.527**	-49.235	17.024**	7.428**	5.437**
		(0.006)	(0.009)	(0.093)	(0.001)	(0.002)	(0.004)

Southern Plains	2.383**	-70.858*		10.639***	6.092**
	(0.001)	(0.044)		(<0.001)	(0.007)

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 10: Direct and indirect DCV impacts on crop variance by region

		(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN								
Central	Direct		-352.577*		-367.645*			
			(0.018)		(0.023)			
	Indirect	23.813**	6.187		-15.951**			-37.001**
		(0.004)	(0.471)		(0.008)			(0.008)
Mountains	Direct		-411.44**	-459.617**	-582.853**	-587.774*	-367.576*	-810.799***
			(0.009)	(0.005)	(0.001)	(0.026)	(0.031)	(<0.001)
	Indirect			-13.747		-87.272**	-53.235**	-72.566**
				(0.501)		(0.004)	(0.004)	(0.008)
Northeast	Direct			672.736***				
				(<0.001)				
	Indirect							
Northern Plains	Direct							
	Indirect			28.073		-98.799**		
				(0.071)		(0.008)		
Pacific	Direct						449.995**	
							(0.004)	
	Indirect	63.062**	23.794**	58.412			427.016**	
		(0.008)	(0.004)	(0.055)			(0.005)	

Southeast	Direct	30.639	28.88						
		(0.099)	(0.071)						
	Indirect			24.049					
				(0.176)					
Southern Plains	Direct								
	Indirect			-4.694*					
				(0.02)					
COTTON									
Central	Direct								
	Indirect								
Mountains	Direct								
	Indirect								
Northeast	Direct								
	Indirect								
Northern Plains	Direct								
	Indirect								
Pacific	Direct								-11069.57*
									(0.021)

	Indirect							
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
SORGHUM								
Central	Direct			-145.436**		-210.794*	-110.876*	-143.377*
				(0.009)		(0.037)	(0.047)	(0.015)
	Indirect							
Mountains	Direct							
	Indirect							
Northeast	Direct							
	Indirect							
Northern Plains	Direct							
	Indirect							

Pacific	Direct							
	Indirect							
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
SOYBEANS								
Central	Direct						-17.47*	
							(0.027)	
	Indirect	-3.348*	-0.027*		6.715*	15.004*		-5.659*
		(0.033)	(0.026)		(0.033)	(0.033)		(0.033)
Mountains	Direct							
	Indirect		4.064*		8.302*	15.084*		
			(0.033)		(0.033)	(0.032)		
Northeast	Direct	21.998*						
		(0.032)						
	Indirect	2.892*	6.166*		10.009*	17.852*	4.518*	0.026*
		(0.03)	(0.033)		(0.032)	(0.032)	(0.033)	(0.026)
Northern Plains	Direct							

	Indirect	-0.032*	3.575*	5.626*	7.282*	14.863*	9.073*	6.612*
		(0.026)	(0.034)	(0.034)	(0.033)	(0.033)	(0.034)	(0.033)
Pacific	Direct							
	Indirect	1.962*	-0.027*	5.19*	6.725*	8.178*	6.401*	2.941*
		(0.033)	(0.026)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
WHEAT								
Central	Direct					122.396**	-67.604*	
						(0.008)	(0.025)	
	Indirect		-66.8*		5.294**	11.52**		
			(0.016)		(0.006)	(0.006)		
Mountains	Direct							
	Indirect		134.363***			-6.716*	12.812*	
			(<0.001)			(0.041)	(0.017)	
Northeast	Direct							
	Indirect		6.137***		7.707**	13.858**		-1.796
			(<0.001)		(0.004)	(0.002)		(0.067)

Northern Plains	Direct							
	Indirect	1.793*	2.841		4.973		8.701**	
		(0.026)	(0.055)		(0.077)		(0.001)	
Pacific	Direct							
	Indirect		3.191**		-3.58**	-7.966**		-7.897**
			(0.001)		(0.002)	(0.002)		(0.009)
Southeast	Direct		-77.675**		-60.04*			
			(0.004)		(0.042)			
	Indirect		4.964***	3.527**	10.806***	17.024**	7.428**	5.437**
			(<0.001)	(0.009)	(<0.001)	(0.001)	(0.002)	(0.004)
Southern Plains	Direct		-70.19*					
			(0.046)					
	Indirect	2.383**	-0.668**		10.639***	6.092**		
		(0.001)	(0.001)		(<0.001)	(0.007)		

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 11: Generalized-least square regression on yield skewness ($\hat{u}^3$)

	Corn	Cotton	Sorghum	Soybeans	Wheat
Trend	479.9	-60321.3	-26.25	4.545	187.3***
	(0.159)	(0.379)	(0.576)	(0.226)	(0.000)
Trend$^{\wedge 2}$	-4.641	145.3	1.590*	-0.143**	-2.829***
	(0.353)	(0.887)	(0.023)	(0.008)	(0.000)
Harvested Acreage	-0.545	-78.20	0.670	-0.0167	0.223
	(0.827)	(0.887)	(0.069)	(0.335)	(0.213)
Temperature	-7581.9	241547.3	2223.5	150.5*	-1590.8**
	(0.203)	(0.932)	(0.055)	(0.023)	(0.002)
Temperature$^{\wedge 2}$	75.05	-1999.8	-22.59*	-1.296*	17.85***
	(0.170)	(0.933)	(0.024)	(0.044)	(0.000)
PDSI	4330.1*	130482.7	-52.01	9.913	41.24
	(0.018)	(0.734)	(0.827)	(0.611)	(0.763)
PDSI$^{\wedge 2}$	-1088.9**	-35443.7	7.040	0.0952	30.01
	(0.009)	(0.703)	(0.892)	(0.982)	(0.329)
Precipitation	736.7	-91643.2	7.612	16.61	98.09
	(0.462)	(0.624)	(0.951)	(0.116)	(0.199)
Precipitation$^{\wedge 2}$	-6.164	882.5	-0.249	-0.108	-1.265
	(0.517)	(0.588)	(0.825)	(0.270)	(0.082)
Day Temp>90°	83.45	1897.6	13.35	-1.138	-4.314
	(0.398)	(0.903)	(0.254)	(0.240)	(0.567)
Day Precip>90	3.549	13707.3	8.916	-3.548*	6.361
	(0.984)	(0.690)	(0.717)	(0.049)	(0.639)
El Niño x R1	14446.0*	-798031.1	-912.6	67.99	281.0
	(0.036)	(0.693)	(0.394)	(0.252)	(0.589)
El Niño x R2	1091.0	-789883.5	-824.9		-971.0
	(0.881)	(0.604)	(0.449)		(0.062)
El Niño x R3	-5053.4		-11693.9	-1.726	615.9
	(0.522)		(0.054)	(0.982)	(0.347)
El Niño x R4	15209.5	-2115382.3	256.9	53.26	95.89
	(0.115)	(0.559)	(0.810)	(0.525)	(0.896)

El Niño x R5	-6303.8 (0.571)	2641032.8 (0.297)	-65.60 (0.975)	3.202 (0.956)	-928.5 (0.272)
El Niño x R6	7520.5 (0.243)	-1348933.2 (0.124)	249.1 (0.742)		360.6 (0.471)
El Niño x R7	3439.3 (0.690)	149364.5 (0.890)	177.8 (0.830)	109.4 (0.148)	-95.18 (0.886)
La Niña x R1	16062.3* (0.027)	-588933.5 (0.783)	477.0 (0.675)	-5.379 (0.932)	43.05 (0.938)
La Niña x R2	-2338.5 (0.762)	-143768.0 (0.930)	-274.8 (0.810)		-644.4 (0.241)
La Niña x R3	-7647.1 (0.357)		-13312.5* (0.028)	-69.95 (0.389)	434.9 (0.529)
La Niña x R4	12843.5 (0.208)	-1802513.0 (0.626)	437.7 (0.697)	44.86 (0.612)	-216.5 (0.780)
La Niña x R5	-653.2 (0.956)	3378343.2 (0.223)	-68.00 (0.976)	-106.7 (0.083)	78.20 (0.931)
La Niña x R6	6056.5 (0.373)	-940015.5 (0.310)	120.5 (0.880)		-81.92 (0.877)
La Niña x R7	5867.2 (0.519)	720074.3 (0.531)	-15.76 (0.986)	137.6 (0.084)	233.1 (0.739)
C1 x R1	4631.5 (0.671)	212681.4 (0.946)	-2195.9 (0.172)	-98.99 (0.296)	-206.9 (0.803)
C2 x R1	20624.9 (0.058)	-2156732.7 (0.448)	-1386.1 (0.371)	89.55 (0.350)	2255.6** (0.006)
C3 x R1	3668.8 (0.741)	1503836.4 (0.656)	-3844.6* (0.029)	155.9 (0.114)	464.3 (0.583)
C4 x R1	21382.1 (0.070)	-1513451.3 (0.649)	-1192.2 (0.479)	73.62 (0.472)	1019.0 (0.256)
C5 x R1	15463.4 (0.390)	2485061.0 (0.672)	-5188.9 (0.104)	52.89 (0.738)	-3485.0* (0.011)
C6 x R1	-10741.9 (0.356)	1139931.7 (0.727)	-3260.2 (0.064)	240.2* (0.020)	1694.1 (0.056)
C7 x R1	5691.5 (0.637)	431103.6 (0.909)	-3621.2 (0.051)	165.9 (0.119)	248.5 (0.786)
C1 x R2	28866.0* (0.013)	1614747.7 (0.517)	-1128.6 (0.521)		-955.9 (0.247)

C2 x R2	48032.2***	-3277899.9	8.923		-5190.4***
	(0.000)	(0.158)	(0.996)		(0.000)
C3 x R2	44734.8***	1678989.5	-2049.2		-235.8
	(0.000)	(0.514)	(0.248)		(0.780)
C4 x R2	54874.3***	1485894.7	-1794.9		-2348.0**
	(0.000)	(0.562)	(0.344)		(0.009)
C5 x R2	56051.8**	3586837.1	1415.6		-226.4
	(0.003)	(0.407)	(0.638)		(0.868)
C6 x R2	30169.1*	2514087.6	1037.4		-502.2
	(0.015)	(0.350)	(0.572)		(0.571)
C7 x R2	67818.9***	1599567.7	-1319.7		-853.9
	(0.000)	(0.567)	(0.509)		(0.356)
C1 x R3	-10700.3			18.79	109.8
	(0.410)			(0.879)	(0.916)
C2 x R3	1729.3			48.03	1512.2
	(0.890)			(0.687)	(0.139)
C3 x R3	-46222.2***		11941.1**	-143.6	-51.38
	(0.001)		(0.006)	(0.246)	(0.961)
C4 x R3	-4627.2		-1325.2	33.81	571.1
	(0.736)		(0.761)	(0.798)	(0.614)
C5 x R3	-22334.0		-6175.7	251.4	230.6
	(0.319)		(0.293)	(0.226)	(0.894)
C6 x R3	-21038.6		10000.5	-154.4	667.7
	(0.138)		(0.135)	(0.227)	(0.543)
C7 x R3	-5785.0		5074.6	88.66	-480.2
	(0.696)		(0.546)	(0.519)	(0.676)
C1 x R4	-10143.7	-1301173.8	25.23	-301.2*	-202.2
	(0.510)	(0.869)	(0.988)	(0.025)	(0.863)
C2 x R4	7405.1		327.1	-40.47	1824.9
	(0.619)		(0.845)	(0.756)	(0.108)
C3 x R4	5943.9	-2646191.3	-1941.6	94.68	-36.80
	(0.703)	(0.737)	(0.262)	(0.489)	(0.975)
C4 x R4	5783.3	-1603447.4	-594.3	-54.36	-83.13
	(0.728)	(0.857)	(0.748)	(0.707)	(0.948)
C5 x R4	11440.2	-1840386.6	-846.4	-148.7	70.50
	(0.652)	(0.845)	(0.762)	(0.501)	(0.971)

C6 x R4	-13986.7	-3611101.1	-2361.4	-183.8	475.3
	(0.393)	(0.658)	(0.193)	(0.201)	(0.700)
C7 x R4	-1045.2	-1376732.6	-11.04	-9.458	-963.3
	(0.951)	(0.865)	(0.995)	(0.949)	(0.456)
C1 x R5	-15480.2	1269681.6	392.0	7.108	-3001.8*
	(0.382)	(0.777)	(0.905)	(0.940)	(0.026)
C2 x R5	14973.2	-5966256.5	1097.6	-29.35	-1120.0
	(0.382)	(0.166)	(0.715)	(0.758)	(0.390)
C3 x R5	1274.8	1927284.0	-577.8	-20.41	-1488.2
	(0.943)	(0.664)	(0.863)	(0.835)	(0.274)
C4 x R5	441.9	-8952904.4	673.9	-107.2	-2436.3
	(0.982)	(0.054)	(0.847)	(0.298)	(0.096)
C5 x R5	14.51	4612252.1	-1982.6	53.63	-1356.1
	(1.000)	(0.490)	(0.755)	(0.729)	(0.542)
C6 x R5	-10083.7	496951.5	-1281.2	59.75	1322.2
	(0.585)	(0.917)	(0.715)	(0.566)	(0.346)
C7 x R5	-3670.4	814507.6	1009.3	59.04	-344.3
	(0.851)	(0.863)	(0.808)	(0.577)	(0.817)
C1 x R6	-6124.6	412989.4	1475.3		423.9
	(0.553)	(0.767)	(0.200)		(0.592)
C2 x R6	10353.2	122159.1	274.4		2339.6**
	(0.314)	(0.931)	(0.814)		(0.003)
C3 x R6	-16784.2	-213654.7	808.8		927.0
	(0.113)	(0.885)	(0.506)		(0.248)
C4 x R6	3881.4	467040.1	-194.0		1487.5
	(0.728)	(0.758)	(0.875)		(0.088)
C5 x R6	965.9	1403077.6	1717.8		1500.6
	(0.955)	(0.558)	(0.372)		(0.249)
C6 x R6	-29585.6**	963331.5	871.7		344.6
	(0.008)	(0.545)	(0.509)		(0.685)
C7 x R6	-10637.6	2552697.2	2313.6		443.4
	(0.354)	(0.113)	(0.075)		(0.615)
C1 x R7	854.6	493078.1	-1246.8	-173.6	497.3
	(0.951)	(0.778)	(0.344)	(0.146)	(0.636)
C2 x R7	9178.3	-1192910.1	-83.24	3.169	2295.5*
	(0.497)	(0.502)	(0.949)	(0.979)	(0.027)

C3 x R7	-6664.4 (0.632)	-398569.6 (0.825)	-493.1 (0.716)	30.94 (0.800)	180.7 (0.864)
C4 x R7	331.0 (0.982)	64261.4 (0.973)	-1140.6 (0.424)	-3.783 (0.977)	1384.4 (0.224)
C5 x R7	9253.0 (0.683)	1631203.9 (0.568)	-2011.2 (0.356)	230.5 (0.244)	591.5 (0.732)
C6 x R7	-23549.4 (0.105)	782888.6 (0.686)	413.1 (0.773)	-269.4^{*} (0.035)	295.6 (0.789)
C7 x R7	621.9 (0.967)	868419.4 (0.652)	-544.3 (0.711)	103.0 (0.435)	-118.8 (0.918)
Constant	131203.4 (0.408)	-5921159.0 (0.945)	-52266.2 (0.124)	-4682.5^{**} (0.006)	29113.1^{*} (0.024)
N	2,634	1,094	1,313	1,885	2,624
Wald $\chi 2$ (d.f.)	730.27 (116) (<0.000)	64.36 (83) (0.9356)	156.84 (91) (<0.000)	207.99 (86) (<0.000)	911.41 (115) (<0.000)

Note: 1) Dependent variable = yearly average crop yield by state. Independent variables=crop acreage, time trend, mean temperature, amount of precipitation, PDSI (Palmer Drought Severity Index), hot days, interactions of ENSO and regional dummies, interactions of DCV and regional dummies, regional dummies, and US state dummies
2) Regional Dummies. R1=Central(IA, IL, IN, MI, MN, MO, OH, WI); R2=Mountains(AZ, CO, ID, MT, NM, NV, UT, WY); R3=Northeast(CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); R4=Northern Plains(KS, ND, NE, SD); R5=Pacific(CA, OR, WA); R6=Southeast(AL, FL, GA, KY, NC, SC, TN, VA, WV); R7=Southern Plains(AR, LA, MS, OK, TX).
3) DCV dummy variables for different DCV phase combinations. C1=(PDO+,TAG-,WPWP-); C2=(PDO-,TAG+,WPWP-); C3=(PDO-,TAG-,WPWP+); C4=(PDO+,TAG-,WPWP+); C5=(PDO+,TAG+,WPWP-); C6=(PDO-,TAG+,WPWP+); and C7=(PDO+,TAG+,WPWP+); where C8=(PDO-,TAG-,WPWP-)is excluded and is in the intercept.
4) Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
5) The dummy coefficients of regions and states are not shown.

Table 12: Total DCV impacts on crop skewness by region

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN							
Central	-1570.639**			1037.299*			2406.317*
	(0.009)			(0.018)			(0.018)
Mountains	28866.01*	48032.22***	45730.71***	54874.29***	61808.03**	33680.3**	72538.11***
	(0.013)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.007)	(<0.001)
Northeast			-46222.18**				
			(0.001)				
Northern Plains			-1902.7		6425.296*		
			(0.093)		(0.018)		
Pacific	-4101.143*	-1569.381**					
	(0.018)	(0.009)					
Southeast						-31025.52**	
						(0.006)	
Southern Plains			314.301*				
			(0.032)				
COTTON							
Central							
Mountains							
Northeast							
Northern Plains							
Pacific							
Southeast							
Southern Plains							
SORGHUM							
Central			-3703.282*	1489.704*	2942.05*	714.767*	-3479.69
			(0.027)	(0.027)	(0.027)	(0.027)	(0.05)

Mountains	-708.323*				-3548.601*		-1758.128*
	(0.027)				(0.027)		(0.027)
Northeast	721.174*	1172.322*	795.288*	2134.537*	3174.945*	1379.883*	
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	
Northern Plains	-3016.358*		-2482.683*	-1718.358*	-2783.811*	-1622.254*	-3468.617*
	(0.027)		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Pacific		722.758*	462.443*	1252.749*	2689.293*	1677.058*	1276.77*
		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Southeast	439.348*		1012.198*	1656.753*	1737.535*	1267.07*	477.356*
	(0.027)		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Southern Plains							
SOYBEANS							
Central	13.259*	26.257*				240.245*	27.565*
	(0.011)	(0.041)				(0.02)	(0.01)
Mountains							
Northeast	-306.702*		33.253*	-22.163	-38.664		-0.291*
	(0.022)		(0.044)	(0.052)	(0.056)		(0.049)
Northern Plains	0.363*						
	(0.049)						
Pacific		0.306*	-11.346			-286.214*	-10.988*
		(0.049)	(0.055)			(0.025)	(0.012)
Southeast							
Southern Plains							
WHEAT							
Central		2255.591**		-161.575**	-3834.916**		
		(0.006)		(0.004)	(0.005)		
Mountains		-5190.392***		-2347.978**	186.512	-498.494**	
		(<0.001)		(0.009)	(0.054)	(0.002)	
Northeast		-209.284***		-238.62**	-436.946**		47.894
		(<0.001)		(0.002)	(0.001)		(0.098)
Northern Plains	-51.154*	-77.12				-306.346***	
	(0.031)	(0.077)				(<0.001)	
Pacific	-3001.77*	-102.925***		112.329**	249.75**		237.128**
	(0.026)	(<0.001)		(0.001)	(0.001)		(0.007)

Southeast		2168.618**	-105.866**	-361.12***	-557.215***	-232.992**	-168.218**
		(0.006)	(0.008)	(<0.001)	(<0.001)	(0.001)	(0.002)
Southern Plains	-77.956***	2319.531*		-360.993***	-184.677**		
	(<0.001)	(0.025)		(<0.001)	(0.005)		

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.

2) Coefficients estimated by Delta method with *p*-values in parentheses ($^{*}\, p < 0.05$, $^{**}\, p < 0.01$, $^{***}\, p < 0.001$).

3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 13: Direct and indirect DCV impacts on crop skewness by region

		(PDO+, TAG-, WPWP-)	**(PDO-, TAG+, WPWP-)**	**(PDO-, TAG-, WPWP+)**	**(PDO+, TAG-, WPWP+)**	**(PDO+, TAG+, WPWP-)**	**(PDO-, TAG+, WPWP+)**	**(PDO+, TAG+, WPWP+)**
CORN								
Central	Direct							
	Indirect	-1570.639**			1037.299*			2406.317*
		(0.009)			(0.018)			(0.018)
Mountains	Direct	28866.01*	48032.22***	44734.83***	54874.29***	56051.81**	30169.1*	67818.87***
		(0.013)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.015)	(<0.001)
	Indirect			995.876		5756.215**	3511.202**	4719.242*
				(0.503)		(0.009)	(0.009)	(0.018)
Northeast	Direct			-46222.18**				
				(0.001)				
	Indirect							
Northern Plains	Direct							
	Indirect			-1902.7		6425.296*		
				(0.093)		(0.018)		
Pacific	Direct							
	Indirect	-4101.143*	-1569.381**					
		(0.018)	(0.009)					

Southeast	Direct		-29585.64**
			(0.008)
	Indirect		-1439.87
			(0.255)
Southern Plains	Direct		
	Indirect	314.301*	
		(0.032)	
COTTON			
Central	Direct		
	Indirect		
Mountains	Direct		
	Indirect		
Northeast	Direct		
	Indirect		
Northern Plains	Direct		
	Indirect		
Pacific	Direct		

	Indirect							
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
SORGHUM								
Central	Direct			-3703.282*				-3479.69
				(0.027)				(0.05)
	Indirect				1489.704*	2942.05*	714.767*	
					(0.027)	(0.027)	(0.027)	
Mountains	Direct							
	Indirect	-708.323*				-3548.601*		-1758.128*
		(0.027)				(0.027)		(0.027)
Northeast	Direct							
	Indirect	721.174*	1172.322*	795.288*	2134.537*	3174.945*	1379.883*	
		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	
Northern Plains	Direct							
	Indirect	-3016.358*		-2482.683*	-1718.358*	-2783.811*	-1622.254*	-3468.617*
		(0.027)		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)

Pacific	Direct							
	Indirect		722.758*	462.443*	1252.749*	2689.293*	1677.058*	1276.77*
			(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Southeast	Direct							
	Indirect	439.348*		1012.198*	1656.753*	1737.535*	1267.07*	477.356*
		(0.027)		(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Southern Plains	Direct							
	Indirect							
				-3703.282*				-3479.69
SOYBEANS								
Central	Direct						240.245*	
							(0.02)	
	Indirect	13.259*	26.257*					27.565*
		(0.011)	(0.041)					(0.01)
Mountains	Direct							
	Indirect							
Northeast	Direct	-301.161*						
		(0.025)						
	Indirect	-5.541		33.253*	-22.163	-38.664		-0.291*
		(0.085)		(0.044)	(0.052)	(0.056)		(0.049)
Northern Plains	Direct							

	Indirect	0.363* (0.049)						
Pacific	Direct						-269.432* (0.035)	
	Indirect		0.306* (0.049)	-11.346 (0.055)			-16.783* (0.03)	-10.988* (0.012)
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
							240.245*	
WHEAT								
Central	Direct		2255.591** (0.006)			-3485.026* (0.011)		
	Indirect				-161.575** (0.004)	-349.891** (0.005)		
Mountains	Direct		-5190.392*** (<0.001)		-2347.978** (0.009)			
	Indirect					186.512 (0.054)	-498.494** (0.002)	
Northeast	Direct							
	Indirect		-209.284*** (<0.001)			-436.946** (0.001)		47.894 (0.098)

Northern Plains	Direct							
	Indirect	-51.154*	-77.12		-238.62**		-306.346***	
		(0.031)	(0.077)		(0.002)		(<0.001)	
Pacific	Direct	-3001.77*						
		(0.026)						
	Indirect		-102.925***		112.329**	249.75**		237.128**
			(<0.001)		(0.001)	(0.001)		(0.007)
Southeast	Direct		2339.615**					
			(0.003)					
	Indirect		-170.998***	-105.866**	-361.12***	-557.215***	-232.992**	-168.218**
			(<0.001)	(0.008)	(<0.001)	(<0.001)	(0.001)	(0.002)
Southern Plains	Direct		2295.501*					
			(0.027)					
	Indirect	-77.956***	24.03***		-360.993***	-184.677**		
		(<0.001)	(<0.001)		(<0.001)	(0.005)		

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 14: Generalized-least square regression on yield kurtosis ($\hat{u}^4$)

	Corn	Cotton	Sorghum	Soybeans	Wheat
Trend	-41417.7	16301124.3	-1825.3	-70.34	-6561.3***
	(0.144)	(0.492)	(0.220)	(0.176)	(0.000)
Trend^2	284.7	27564.1	69.67**	2.120**	94.22***
	(0.494)	(0.938)	(0.002)	(0.004)	(0.000)
Harvested Acreage	107.7	1863.4	22.42	0.241	-5.879
	(0.603)	(0.992)	(0.055)	(0.316)	(0.313)
Temperature	667472.5	-42903286.8	67457.3	-2432.3**	57015.2***
	(0.178)	(0.672)	(0.067)	(0.008)	(0.001)
Temperature^2	-6417.7	510613.9	-711.0*	21.58*	-626.5***
	(0.158)	(0.745)	(0.025)	(0.015)	(0.000)
PDSI	-243232.5	45524614.7	-5920.9	-118.7	-1042.7
	(0.111)	(0.732)	(0.433)	(0.660)	(0.815)
PDSI^2	64849.3	-5239118.5	979.1	-4.264	-802.8
	(0.060)	(0.870)	(0.550)	(0.942)	(0.422)
Precipitation	-87818.9	50896231.5	1692.7	-255.0	-3436.4
	(0.292)	(0.430)	(0.668)	(0.081)	(0.167)
Precipitation^2	786.7	-492534.3	-15.56	1.829	42.02
	(0.319)	(0.380)	(0.663)	(0.177)	(0.076)
Day Temp>90°	-14936.7	1327691.5	554.5	14.87	141.6
	(0.069)	(0.806)	(0.135)	(0.268)	(0.563)
Day Precip>90	-5483.0	-9387322.7	348.8	41.79	-223.3
	(0.708)	(0.431)	(0.655)	(0.094)	(0.613)
El Niño x R1	-1082980.5	178806292.8	-27360.9	-1135.4	-11934.2
	(0.058)	(0.798)	(0.420)	(0.167)	(0.480)
El Niño x R2	128751.2	880693532.7	-34531.5		37410.3*
	(0.832)	(0.095)	(0.317)		(0.027)
El Niño x R3	414607.8		-514865.3**	-33.72	-16419.8
	(0.528)		(0.007)	(0.975)	(0.441)
El Niño x R4	-1064319.4	554641989.1	14307.5	-1157.9	-5707.0
	(0.185)	(0.632)	(0.672)	(0.318)	(0.811)

El Niño x R5	297029.7 (0.748)	-1.68818e+09 (0.054)	-5056.6 (0.939)	-25.40 (0.975)	19474.6 (0.479)
El Niño x R6	-612992.6 (0.252)	639325363.6* (0.035)	5645.5 (0.814)		-12575.6 (0.439)
El Niño x R7	-80642.8 (0.911)	12352316.8 (0.974)	2129.0 (0.935)	-1775.2 (0.090)	1609.3 (0.941)
La Niña x R1	-1217291.5* (0.043)	74733773.8 (0.919)	16159.7 (0.654)	-109.3 (0.900)	-6007.4 (0.737)
La Niña x R2	585610.6 (0.361)	146791104.9 (0.795)	-7912.9 (0.827)		31651.0 (0.076)
La Niña x R3	627067.4 (0.363)		-548545.8** (0.004)	925.8 (0.410)	-11271.9 (0.616)
La Niña x R4	-882491.4 (0.298)	399864630.0 (0.749)	15799.8 (0.657)	-1067.9 (0.383)	3954.6 (0.875)
La Niña x R5	92262.1 (0.925)	-1.69267e+09 (0.077)	-3233.2 (0.963)	1548.4 (0.069)	-9396.7 (0.747)
La Niña x R6	-598467.1 (0.290)	458978336.7 (0.152)	-1855.5 (0.942)		1604.9 (0.925)
La Niña x R7	-215884.5 (0.776)	-238934098.4 (0.548)	5794.1 (0.834)	-1928.7 (0.080)	-3992.3 (0.861)
C1 x R1	30936.0 (0.973)	-131825502.7 (0.903)	-81303.6 (0.111)	1561.5 (0.234)	6168.2 (0.819)
C2 x R1	-1293667.8 (0.153)	655987042.7 (0.505)	-50866.7 (0.300)	-1238.5 (0.351)	-71434.5** (0.007)
C3 x R1	23128.8 (0.980)	-349315357.0 (0.765)	-140300.3* (0.012)	-2324.6 (0.089)	-10829.4 (0.693)
C4 x R1	-1281858.3 (0.191)	407059175.3 (0.723)	-43451.2 (0.415)	-1042.4 (0.463)	-29379.7 (0.314)
C5 x R1	-862780.6 (0.564)	-735772912.6 (0.717)	-179609.1 (0.076)	-1612.3 (0.462)	89542.3* (0.044)
C6 x R1	1223304.7 (0.207)	-474495696.0 (0.675)	-125314.3* (0.025)	-3285.7* (0.022)	-43219.4 (0.134)
C7 x R1	-40661.3 (0.968)	-194904119.2 (0.882)	-134329.1* (0.022)	-2155.5 (0.143)	-1378.3 (0.963)
C1 x R2	-2513122.5** (0.009)	-733657556.3 (0.394)	-30836.4 (0.580)		33277.9 (0.215)

C2 x R2	-4878321.6***	1.52400e+09	-3621.7		190881.5***
	(0.000)	(0.058)	(0.946)		(0.000)
C3 x R2	-3688909.6***	-606487053.1	-69502.4		7824.1
	(0.000)	(0.494)	(0.217)		(0.776)
C4 x R2	-4933761.6***	78188520.3	-51387.4		92853.5**
	(0.000)	(0.930)	(0.392)		(0.001)
C5 x R2	-4875403.7**	-870463188.7	23489.0		17068.5
	(0.002)	(0.560)	(0.805)		(0.701)
C6 x R2	-2464162.3*	-1.00449e+09	39046.9		11096.8
	(0.017)	(0.278)	(0.502)		(0.700)
C7 x R2	-5741411.1***	-641984221.6	-41813.4		29468.1
	(0.000)	(0.503)	(0.509)		(0.327)
C1 x R3	677084.7			-212.9	-2108.4
	(0.531)			(0.901)	(0.950)
C2 x R3	-207381.7			-673.9	-55050.2
	(0.842)			(0.683)	(0.097)
C3 x R3	3409788.4**		451915.2***	1983.3	1066.7
	(0.002)		(0.001)	(0.248)	(0.975)
C4 x R3	297399.9		-81865.0	-338.0	-20011.3
	(0.795)		(0.553)	(0.854)	(0.587)
C5 x R3	1569909.3		-223609.0	-3169.4	-8311.1
	(0.399)		(0.230)	(0.270)	(0.883)
C6 x R3	1321448.7		396550.5	2966.7	-19928.9
	(0.262)		(0.062)	(0.094)	(0.576)
C7 x R3	575477.1		283764.1	-1396.5	12507.0
	(0.640)		(0.286)	(0.464)	(0.737)
C1 x R4	795759.3	-28420393.7	944.1	3965.5*	12892.0
	(0.535)	(0.987)	(0.986)	(0.033)	(0.735)
C2 x R4	-725990.2		10618.1	292.3	-58456.6
	(0.558)		(0.841)	(0.871)	(0.113)
C3 x R4	-223147.4	410308238.7	-71352.0	-1544.1	1311.4
	(0.863)	(0.807)	(0.193)	(0.415)	(0.973)
C4 x R4	-452974.0	92487818.0	-17741.6	331.8	-865.9
	(0.744)	(0.967)	(0.762)	(0.868)	(0.983)
C5 x R4	-538754.3		-43092.5	1855.2	2598.2
	(0.798)		(0.627)	(0.544)	(0.967)

C6 x R4	1090184.5 (0.423)	624088373.9 (0.743)	-92779.4 (0.106)	2733.1 (0.170)	-17011.4 (0.672)
C7 x R4	149612.5 (0.916)	-69241243.4 (0.972)	-16969.9 (0.777)	-148.9 (0.942)	26158.9 (0.534)
C1 x R5	939448.7 (0.524)	-583774063.2 (0.707)	9494.1 (0.927)	-23.47 (0.986)	108025.1* (0.014)
C2 x R5	-851630.3 (0.550)	1.99529e+09 (0.181)	16874.7 (0.859)	502.5 (0.703)	11556.0 (0.785)
C3 x R5	245568.0 (0.869)	-925945689.9 (0.547)	-38942.4 (0.713)	110.5 (0.935)	36623.6 (0.407)
C4 x R5	-21260.5 (0.989)	3.98873e+09* (0.013)	10993.8 (0.921)	1440.3 (0.313)	80889.9 (0.089)
C5 x R5	720339.4 (0.767)	-2.17817e+09 (0.346)	-73307.0 (0.716)	-814.2 (0.705)	25896.1 (0.720)
C6 x R5	905250.7 (0.555)	-530490989.5 (0.747)	-54114.4 (0.626)	-1271.2 (0.378)	-39721.3 (0.383)
C7 x R5	619504.2 (0.703)	-456552316.1 (0.780)	-5344.4 (0.968)	-1018.3 (0.488)	10710.6 (0.825)
C1 x R6	326329.7 (0.704)	26315963.2 (0.956)	45396.5 (0.214)		-9908.2 (0.700)
C2 x R6	-794409.0 (0.353)	-11360688.5 (0.981)	2263.9 (0.951)		-72810.9** (0.004)
C3 x R6	1186584.1 (0.178)	288778038.2 (0.572)	11685.5 (0.762)		-21597.5 (0.408)
C4 x R6	-378973.8 (0.683)	-95143951.9 (0.856)	-13759.4 (0.725)		-40610.0 (0.152)
C5 x R6	-30827.2 (0.983)	-403245030.0 (0.627)	36626.5 (0.548)		-36905.7 (0.383)
C6 x R6	2451930.4** (0.008)	-376037115.2 (0.495)	22533.0 (0.590)		-8348.9 (0.762)
C7 x R6	872536.0 (0.360)	-946673551.4 (0.089)	93796.2* (0.023)		-10152.2 (0.723)
C1 x R7	93021.3 (0.935)	-213255558.0 (0.725)	-33515.4 (0.422)	2056.3 (0.214)	-9971.0 (0.770)
C2 x R7	-570637.8 (0.611)	470097900.2 (0.445)	-2258.9 (0.957)	-358.4 (0.827)	-70217.2* (0.037)

C3 x R7	803366.5 (0.487)	157277130.2 (0.801)	-30431.4 (0.479)	-1077.7 (0.524)	-965.6 (0.978)
C4 x R7	80924.3 (0.948)	-668208.4 (0.999)	-35717.3 (0.430)	-278.9 (0.877)	-39728.0 (0.283)
C5 x R7	-189519.3 (0.920)	-572869055.6 (0.562)	-68525.5 (0.321)	-3720.2 (0.175)	-12821.2 (0.819)
C6 x R7	1718294.6 (0.154)	-364377071.0 (0.587)	23036.8 (0.612)	3842.7^{*} (0.030)	-8114.7 (0.821)
C7 x R7	428486.1 (0.733)	-316550521.0 (0.635)	-20798.8 (0.655)	-1857.0 (0.309)	9102.9 (0.808)
Constant	-12175327.9 (0.356)	-9.76e+09 0.753	-1562204.3 (0.146)	72721.7^{**} (0.002)	-1085605.4^{**} (0.010)
N	2,634	1,094	1,313	1,885	2,624
Wald $\chi 2$ (d.f.)	736.79 (116) (<0.000)	195.94 (82) (<0.000)	196.90 (91) (<0.000)	228.36 (86) (<0.000)	1001.97 (115) (<0.000)

Note: 1) Dependent variable = yearly average crop yield by state. Independent variables=crop acreage, time trend, mean temperature, amount of precipitation, PDSI (Palmer Drought Severity Index), hot days, interactions of ENSO and regional dummies, interactions of DCV and regional dummies, regional dummies, and US state dummies
2) Regional Dummies. R1=Central(IA, IL, IN, MI, MN, MO, OH, WI); R2=Mountains(AZ, CO, ID, MT, NM, NV, UT, WY); R3=Northeast(CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT); R4=Northern Plains(KS, ND, NE, SD); R5=Pacific(CA, OR, WA); R6=Southeast(AL, FL, GA, KY, NC, SC, TN, VA, WV); R7=Southern Plains(AR, LA, MS, OK, TX).
3) DCV dummy variables for different DCV phase combinations. C1=(PDO+,TAG-,WPWP-); C2=(PDO-,TAG+,WPWP-); C3=(PDO-,TAG-,WPWP+); C4=(PDO+,TAG-,WPWP+); C5=(PDO+,TAG+,WPWP-); C6=(PDO-,TAG+,WPWP+); and C7=(PDO+,TAG+,WPWP+); where C8=(PDO-,TAG-,WPWP-)is excluded and is in the intercept.
4) Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
5) The dummy coefficients of regions and states are not shown.

Table 15: Total DCV impacts on crop kurtosis by region

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN							
Central							
Mountains	-2513123**	-4878322***	-3688910***	-4933762***	-4875404**	-2464162*	-5741411***
	(0.009)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.017)	(<0.001)
Northeast			3409788**				
			(0.002)				
Northern Plains							
Pacific							
Southeast						2451930**	
						(0.008)	
Southern Plains							
COTTON							
Central							
Mountains							
Northeast							
Northern Plains							
Pacific							
Southeast							
Southern Plains							
SORGHUM							
Central			-136102**	45760.57*	90373.57*	-100284	-130463.2*
			(0.009)	(0.029)	(0.029)	(0.059)	(0.018)

Mountains	-21758.16*				-109005.5*		-54005.98*
	(0.029)				(0.029)		(0.029)
Northeast	22152.91*	36011.26*	24429.56*	65568.46*	97527.61*	42387.11*	
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	
Northern Plains	-92656.15*		-76262.76*	-52784.33*	-85512.78*	-49832.21*	-106548.6*
	(0.029)		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Pacific		22201.59*	14205.27*	38481.81*	82609.41*	51515.66*	128042.3**
		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.003)
Southeast	13495.83*		31092.58*	50891.96*	53373.41*	38921.71*	14663.36*
	(0.029)		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Southern Plains							
SOYBEANS							
Central	-198.056**	-432.176*				-3285.719*	-420.589**
	(0.006)	(0.015)				(0.022)	(0.005)
Mountains							
Northeast	4030.514*		-553.735*	296.872	516.514		
	(0.03)		(0.015)	(0.06)	(0.066)		
Northern Plains							
Pacific			154.053			4083.4*	165.194**
			(0.06)			(0.021)	(0.007)
Southeast							
Southern Plains							
WHEAT							
Central		-71434.45**		4974.692**	100274.9*		
		(0.007)		(0.007)	(0.024)		
Mountains		190881.5***		92853.49**	-5310	17865.99**	
		(<0.001)		(0.001)	(0.091)	(0.001)	
Northeast		6958.432***		7426.819**	13780.57**		
		(<0.001)		(0.003)	(0.001)		
Northern Plains	1491.897					10387.67***	
	(0.053)					(<0.001)	
Pacific	108025.1*	3298.51***		-3530.873**	-7844.946**		-7209.983*
	(0.014)	(<0.001)		(0.002)	(0.002)		(0.012)

Southeast		-67089.49**	3218.154*	11852.44***	18037.56***	7321.149**	5232.496**
		(0.009)	(0.012)	(<0.001)	(<0.001)	(0.002)	(0.004)
Southern Plains	2523.021***	-71042.65*		11964.59***	5656.79**		-2139.79
	(<0.001)	(0.035)		(<0.001)	(0.009)		(0.065)

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Table 16: Direct and indirect DCV impacts on crop kurtosis by region

		(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)
CORN								
Central	Direct							
	Indirect							
Mountains	Direct	-2513123** (0.009)	-4878322*** (<0.001)	-3688910*** (<0.001)	-4933762*** (<0.001)	-4875404** (0.002)	-2464162* (0.017)	-5741411*** (<0.001)
	Indirect							
Northeast	Direct			3409788** (0.002)				
	Indirect							
Northern Plains	Direct							
	Indirect							
Pacific	Direct							
	Indirect							

Southeast	Direct	2451930**
		(0.008)
	Indirect	
Southern Plains	Direct	
	Indirect	
COTTON		
Central	Direct	
	Indirect	
Mountains	Direct	
	Indirect	
Northeast	Direct	
	Indirect	
Northern Plains	Direct	
	Indirect	
Pacific	Direct	

	Indirect							
Southeast	Direct							
	Indirect							
Southern Plains	Direct							
	Indirect							
SORGHUM								
Central	Direct			-136102**			-122240.4*	-130463.2*
				(0.009)			(0.02)	(0.018)
	Indirect				45760.57*	90373.57*	21956.11*	
					(0.029)	(0.029)	(0.029)	
Mountains	Direct							
	Indirect	-21758.16*				-109005.5*		-54005.98*
		(0.029)				(0.029)		(0.029)
Northeast	Direct							
	Indirect	22152.91*	36011.26*	24429.56*	65568.46*	97527.61*	42387.11*	
		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	
Northern Plains	Direct							
	Indirect	-92656.15*		-76262.76*	-52784.33*	-85512.78*	-49832.21*	-106548.6*
		(0.029)		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)

Pacific	Direct							88822.6*
								(0.022)
	Indirect		22201.59*	14205.27*	38481.81*	82609.41*	51515.66*	39219.68*
			(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Southeast	Direct							
	Indirect	13495.83*		31092.58*	50891.96*	53373.41*	38921.71*	14663.36*
		(0.029)		(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Southern Plains	Direct							
	Indirect							
				-136102**			-122240.4*	-130463.2*
SOYBEANS								
Central	Direct						-3285.719*	
							(0.022)	
	Indirect	-198.056**	-432.176*					-420.589**
		(0.006)	(0.015)					(0.005)
Mountains	Direct							
	Indirect							
Northeast	Direct	3965.546*						
		(0.033)						
	Indirect	64.968		-553.735*	296.872	516.514		
		(0.143)		(0.015)	(0.06)	(0.066)		
Northern Plains	Direct							

	Indirect						
Pacific	Direct					3842.651*	
						(0.03)	
	Indirect		154.053			240.749*	165.194**
			(0.06)			(0.024)	(0.007)
Southeast	Direct						
	Indirect						
Southern Plains	Direct						
	Indirect						
						-3285.719*	
WHEAT							
Central	Direct	-71434.45**			89542.31*		
		(0.007)			(0.044)		
	Indirect			4974.692**	10732.59**		
				(0.007)	(0.008)		
Mountains	Direct	190881.5***		92853.49**			
		(<0.001)		(0.001)			
	Indirect				-5310	17865.99**	
					(0.091)	(0.001)	
Northeast	Direct						
	Indirect	6958.432***		7426.819**	13780.57**		
		(<0.001)		(0.003)	(0.001)		

Northern Plains	Direct							
	Indirect	1491.897					10387.67***	
		(0.053)					(<0.001)	
Pacific	Direct	108025.1*						
		(0.014)						
	Indirect		3298.51***		-3530.873**	-7844.946**		-7209.983*
			(<0.001)		(0.002)	(0.002)		(0.012)
Southeast	Direct		-72810.86**					
			(0.004)					
	Indirect		5721.368***	3218.154*	11852.44***	18037.56***	7321.149**	5232.496**
			(<0.001)	(0.012)	(<0.001)	(<0.001)	(0.002)	(0.004)
Southern Plains	Direct		-70217.18*					
			(0.037)					
	Indirect	2523.021***	-825.467***		11964.59***	5656.79**		-2139.79
		(<0.001)	(<0.001)		(<0.001)	(0.009)		(0.065)

Note: 1) Yields of all crops are in bushels/ harvested acre, except for cotton yield which is in lbs/ harvested acre.
2) Coefficients estimated by Delta method with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
3) Blanks in some regions imply no significant impacts at 95% statistical confidence.

Figure 2: Total marginal effects of DCV phase combinations on corn yields (%)

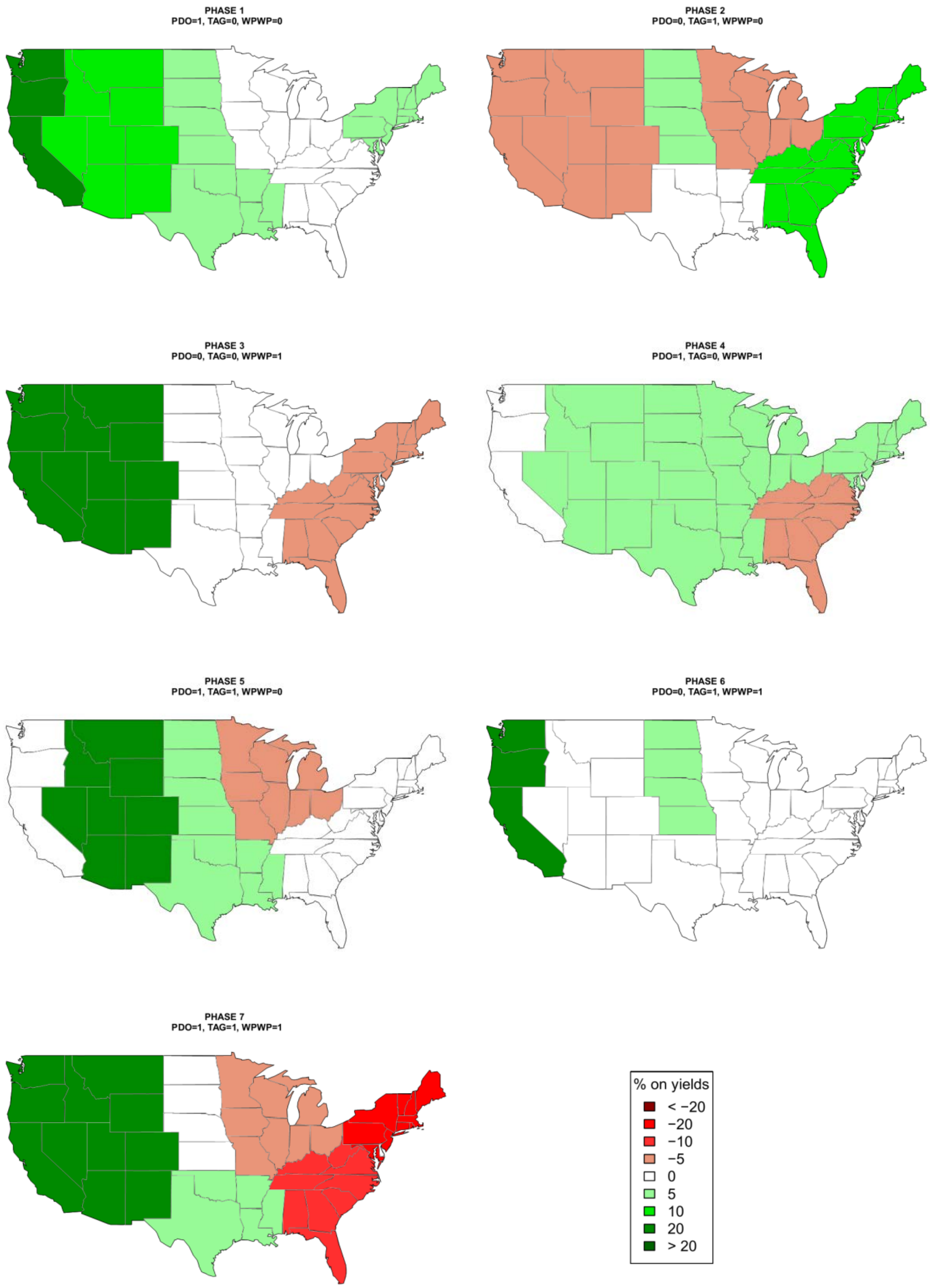


Figure 3: Total marginal effects of DCV phase combinations on cotton yields (%)

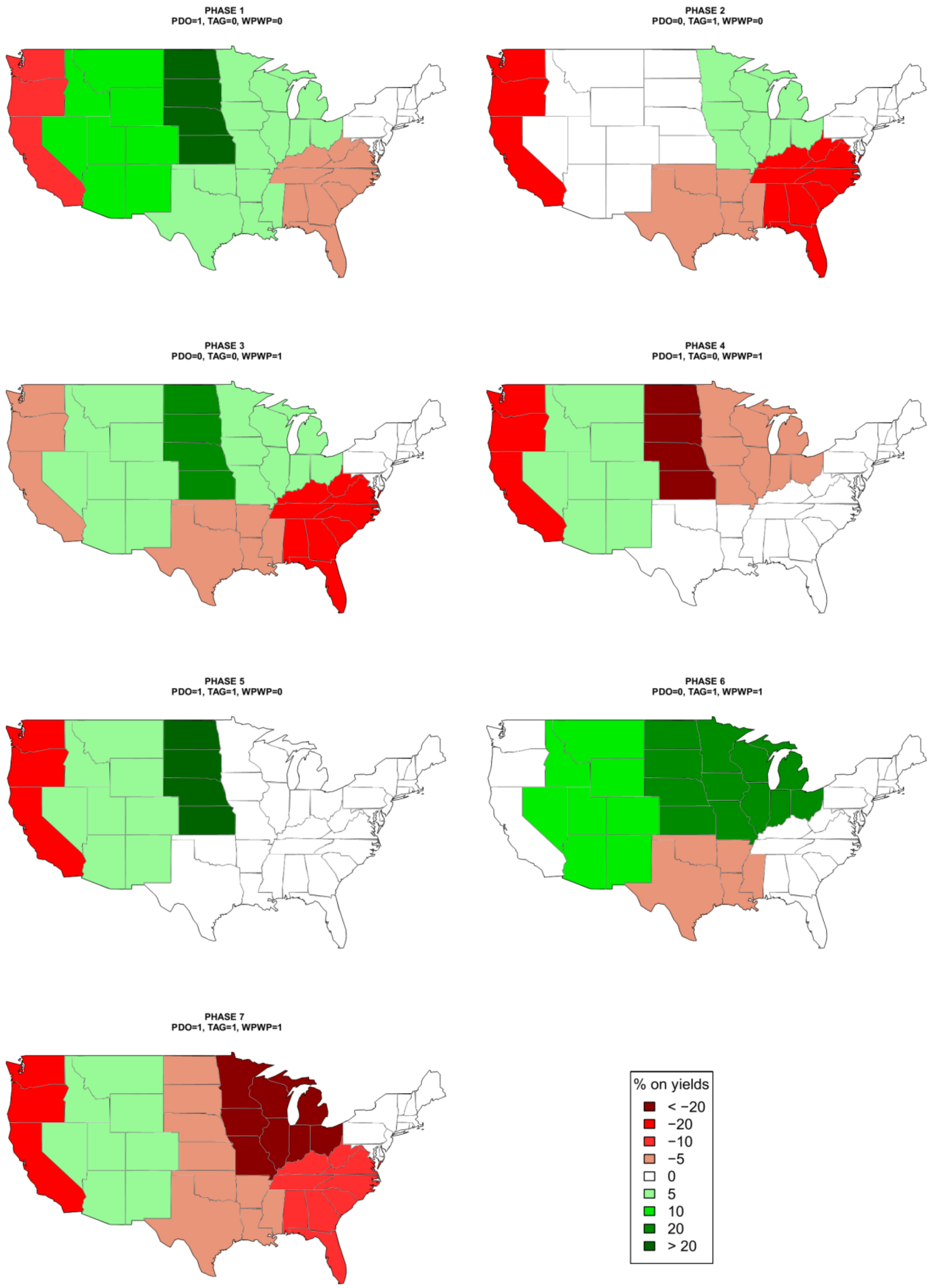


Figure 4: Total marginal effects of DCV phase combinations on sorghum yields (%)

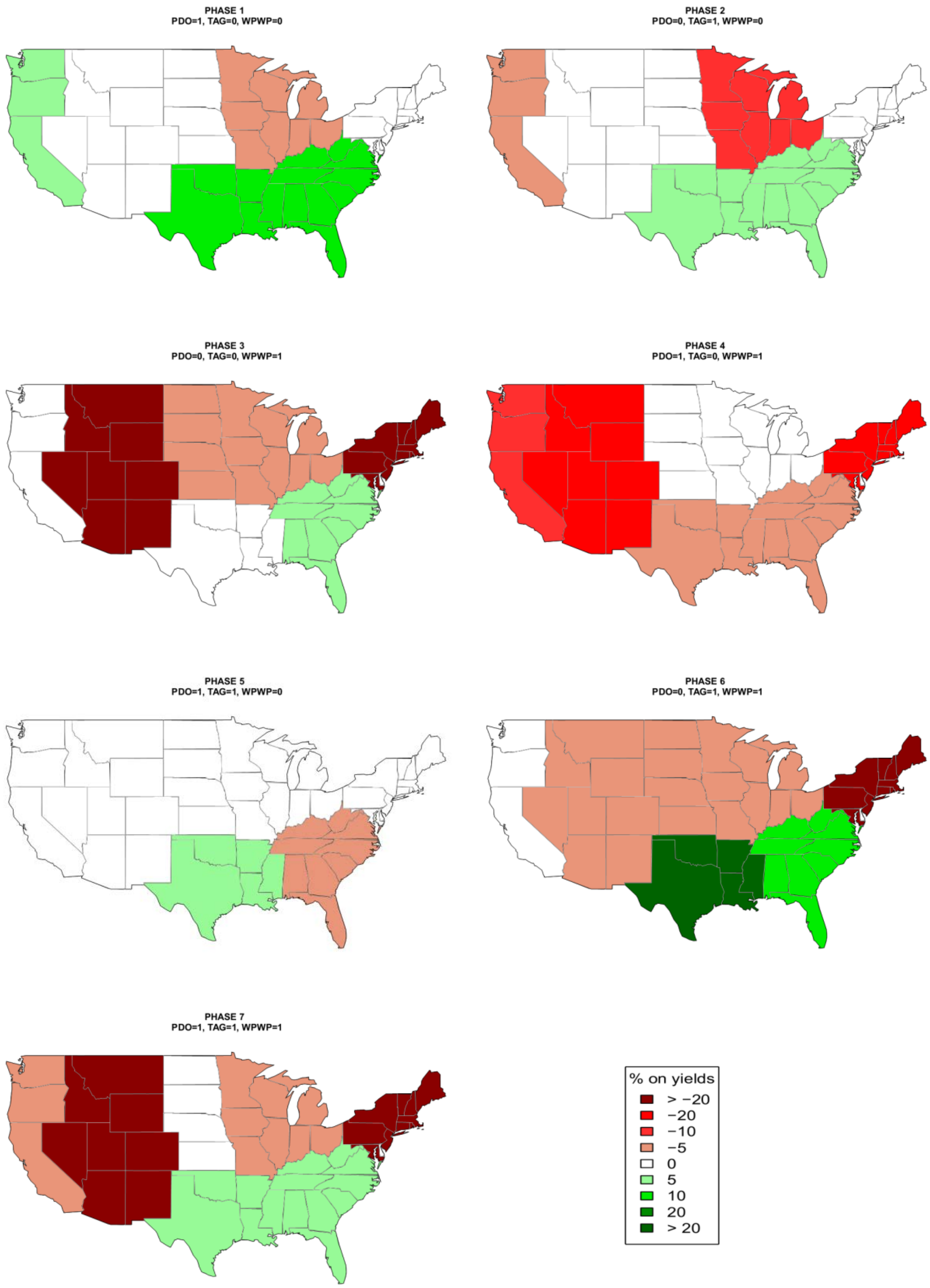


Figure 5: Total marginal effects of DCV phase combinations on soybeans yields (%)

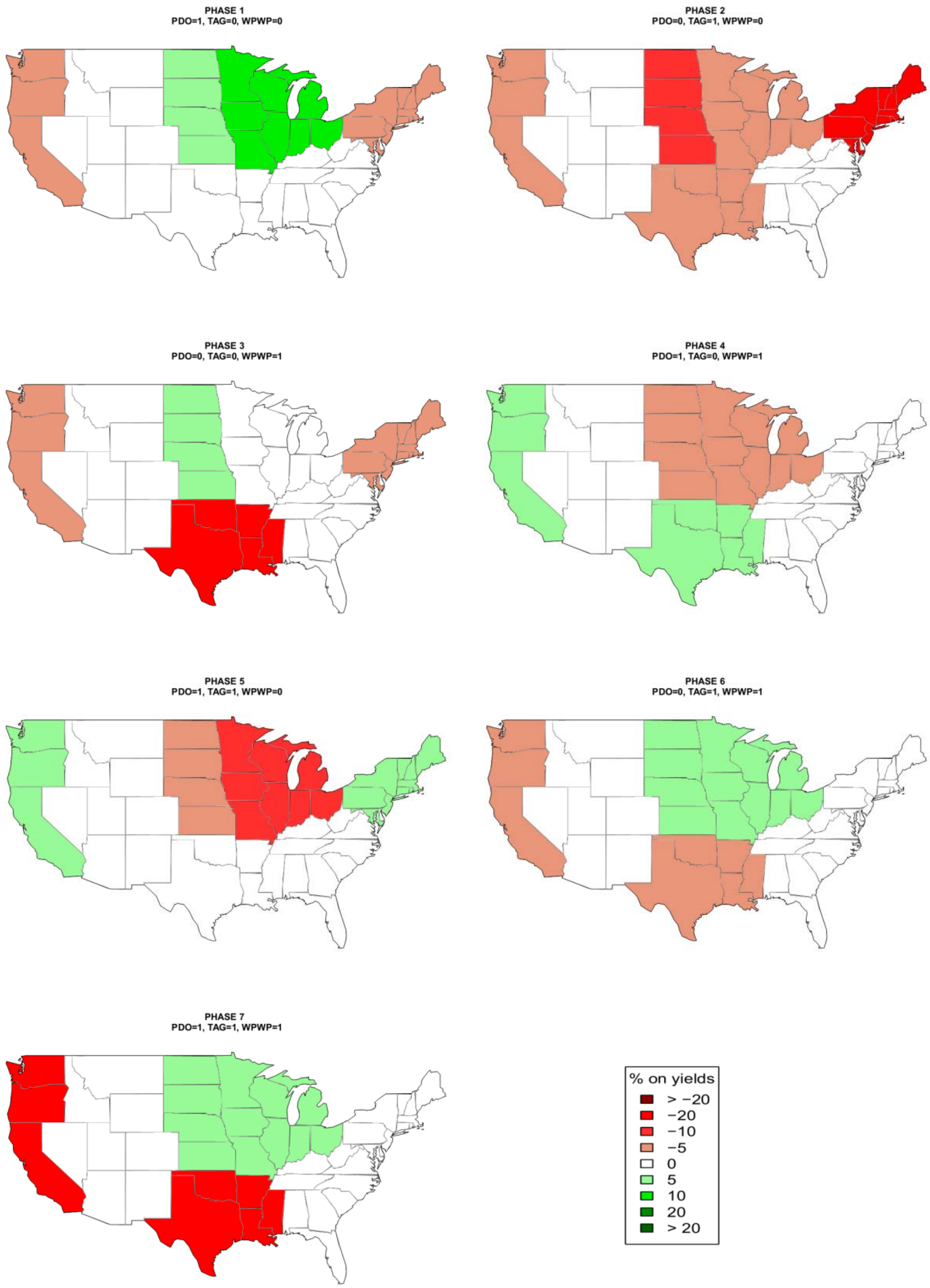


Figure 6: Total marginal effects of DCV phase combinations on wheat yields (%)

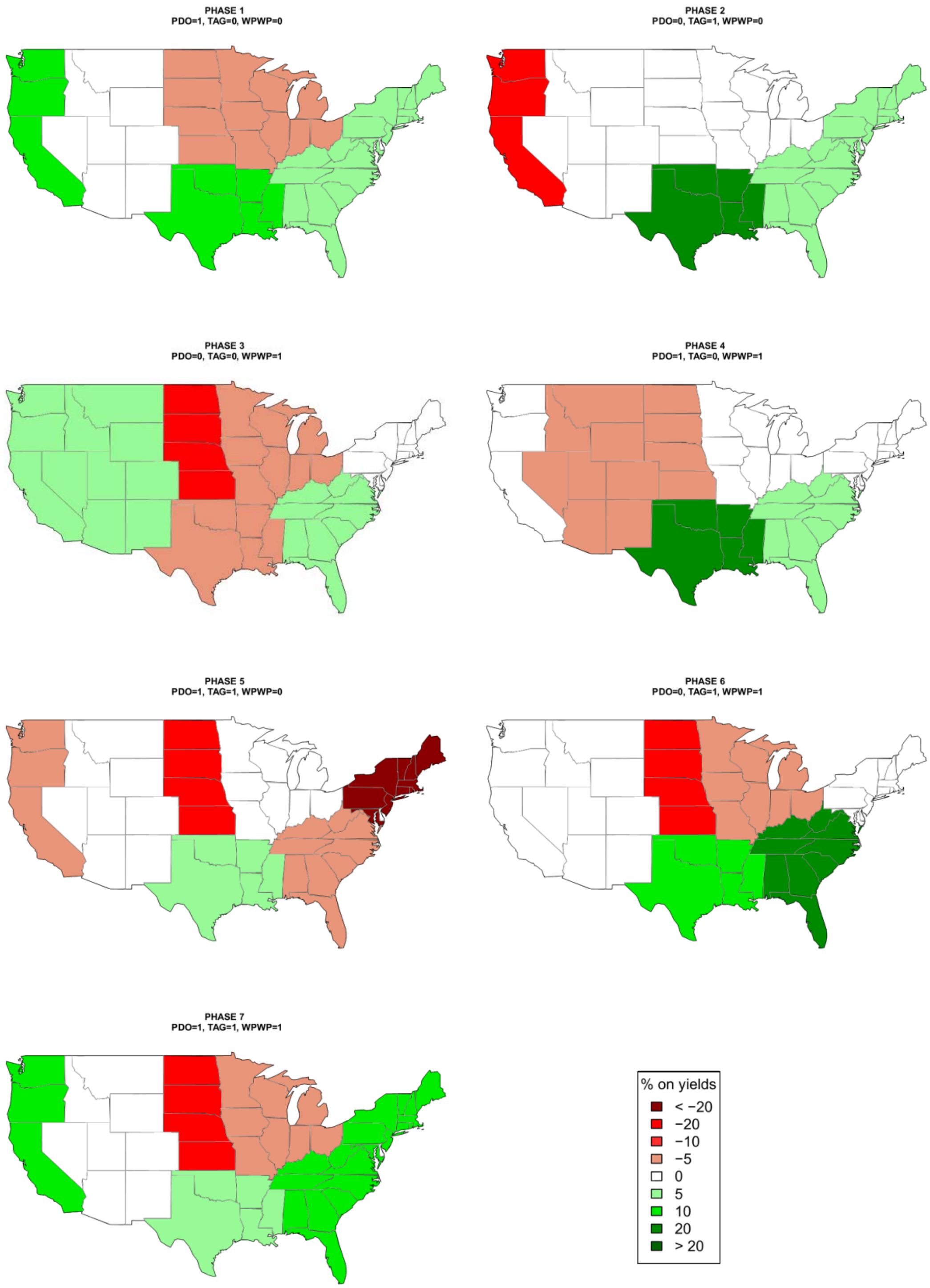
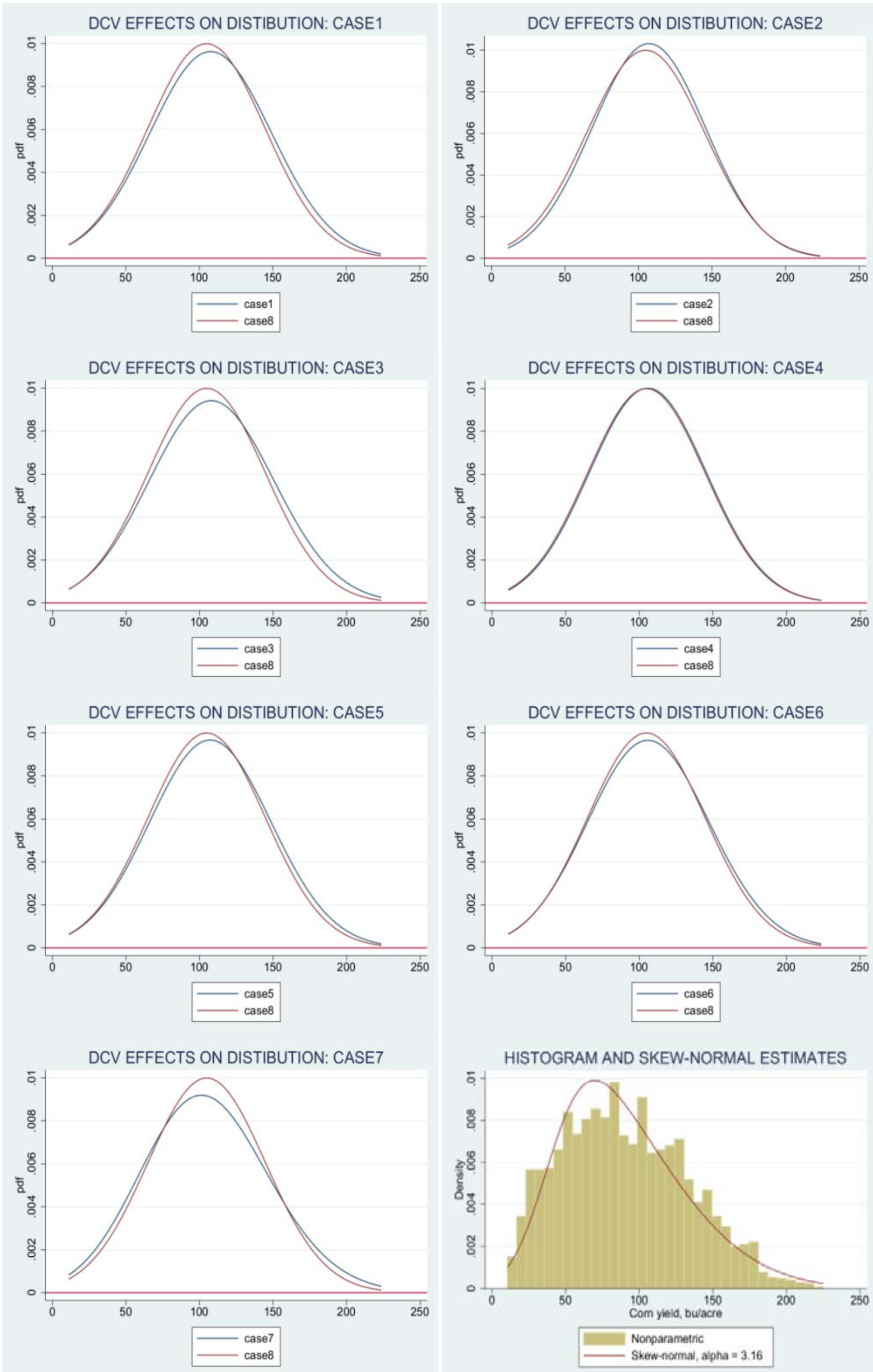


Table 17: Total DCV effects on US crop yield distribution moments

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO-, TAG-, WPWP-)
CORN								
Mean in bsh/acre	164.00	164.00	163.99	163.93	163.91	163.94	163.92	163.91
Standard deviation	17.76	17.55	17.80	17.68	17.68	17.73	17.73	17.68
Skewness	0.118***	0.08***	0.119***	0.1***	0.103***	0.115***	0.109***	0.103***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
COTTON								
Mean in lbs/acre	1,038.81	1,036.58	1,037.87	1,038.09	1,038.34	1,038.73	1,037.9	1,038.33
Standard deviation	192.31	191.88	192.3	192.38	192.41	192.43	192.49	192.46
Skewness	0.629***	0.628***	0.631***	0.623***	0.626***	0.628***	0.625***	0.625***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SORGHUM								
Mean in bsh /acre	75.24	75.21	75.12	75.14	75.19	75.23	75.17	75.19
Standard deviation	15.97	15.93	15.97	16.02	16.03	15.98	16.03	16.03
Skewness	0.718***	0.712***	0.721***	0.716***	0.714***	0.711***	0.717***	0.714***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean in bsh /acre	43.16	43.09	43.14	43.16	43.16	43.16	43.15	43.16
Standard deviation	3.98	3.96	3.98	3.96	3.96	3.97	3.98	3.96
Skewness	0.149***	0.146***	0.152***	0.133***	0.127***	0.139***	0.132***	0.128***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
WHEAT								
Mean in bsh /acre	64.12	64.13	64.08	64.1	64.09	64.12	64.1	64.09
Standard deviation	11.61	11.57	11.64	11.62	11.62	11.6	11.63	11.63
Skewness	0.859***	0.871***	0.858***	0.858***	0.857***	0.857***	0.857***	0.857***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Note: 1) Skewness indexes with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Calculations are fixed at year 2012 for time and harvested acres.

Figure 7: Example for DCV impacts on national yield distribution of corn



Note: Underlying figures are the average value of corn yield in 1950-2012 which evaluated from different DCV phase combinations. The regressions also include DCV by region fixed effects and regional and state fixed effects.

Table 18: Output distribution moments estimated with log skew-normal

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	363,092***	362,490***	362,661***	363,159***	363,041***	362,669***	362,836***	360,933***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	632,804	622,318	636,298	632,076	634,682	635,315	633,624	630,414
	(0.055)	(0.053)	(0.056)	(0.055)	(0.055)	(0.056)	(0.055)	(0.055)
Skewness	17.38	16.84	17.63	17.34	17.5	17.57	17.46	17.46
	(0.055)	(0.053)	(0.056)	(0.055)	(0.055)	(0.056)	(0.055)	(0.055)
COTTON								
Mean	794,448**	799,329**	790,206**	793,045**	793,840**	791,523**	792,307**	793,831**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Standard deviation	913,583	914,948	911,107	913,132	911,780	908,664	915,947	912,098
	(0.078)	(0.078)	(0.075)	(0.078)	(0.078)	(0.078)	(0.072)	(0.078)
Skewness	4.37	4.38	4.26	4.38	4.36	4.36	4.2	4.36
	(0.078)	(0.078)	(0.075)	(0.078)	(0.078)	(0.078)	(0.072)	(0.078)
SORGHUM								
Mean	74,574	77,908***	71,651***	71,535***	71,658***	71,648***	71,651***	82,631***
	(0.827)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	79,700	80,296***	79,102***	78,958***	79,104***	79,102***	79,102***	92,320***
	(0.852)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.13	1.07***	1.19***	1.19***	1.19***	1.19***	1.19***	1.21***
	(0.852)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	107,804***	107,513***	107,870***	107,844***	107,701***	107,818***	107,788***	107,092***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	119,779*	116,643*	121,471*	119,133*	119,417*	120,318*	120,078*	118,895*
	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
Skewness	7.53*	7.24*	7.69*	7.46*	7.5*	7.58*	7.56*	7.52*
	(0.018)	(0.016)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
WHEAT								
Mean	91,647***	92,286***	91,837***	92,068***	91,925***	92,077***	91,770***	91,957***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	133,580**	134,267**	133,689**	133,987**	133,878**	133,847**	133,702**	133,886**
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Skewness	3.71**	3.84**	3.74**	3.79**	3.76**	3.77**	3.75**	3.76**
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)

Note: 1) Estimated output distribution moments with p-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Outputs of all crops are in thousand bushels, except cotton which is in thousand lbs.

Table 19: Output distribution moments under ENSO (Neutral)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	374,415***	372,818***	374,549***	374,565***	374,420***	374,584***	374,324***	374,452***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	734,614	712,656	744,898	735,028	737,080	744,203	737,287	737,176
	(0.074)	(0.067)	(0.078)	(0.074)	(0.074)	(0.077)	(0.075)	(0.074)
Skewness	22.5	21.23	23.21	22.51	22.67	23.15	22.7	22.67
	(0.074)	(0.067)	(0.078)	(0.074)	(0.074)	(0.077)	(0.075)	(0.074)
COTTON								
Mean	775,769**	786,366**	771,047**	774,383**	775,135**	772,995**	772,693**	775,126**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Standard deviation	916,713	912,776	914,252	916,044	914,924	911,962	919,141	915,196
	(0.061)	(0.061)	(0.06)	(0.062)	(0.061)	(0.062)	(0.058)	(0.061)
Skewness	4.21	4.19	4.15	4.22	4.2	4.2	4.12	4.2
	(0.061)	(0.061)	(0.06)	(0.062)	(0.061)	(0.062)	(0.058)	(0.061)
SORGHUM								
Mean	72,589***	72,471***	72,594***	75,493	74,585***	72,588***	72,589***	72,596***
	(<0.001)	(<0.001)	(<0.001)	(0.662)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	80,093***	80,067***	80,099***	80,686	80,555**	80,092***	80,093***	80,094***
	(<0.001)	(<0.001)	(<0.001)	(0.787)	(0.003)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.19***	1.19***	1.19***	1.13	1.15**	1.19***	1.19***	1.19***
	(<0.001)	(<0.001)	(<0.001)	(0.787)	(0.003)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	105,672***	105,239***	105,774***	105,730***	105,580***	105,794***	105,652***	105,575***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	129,359*	124,797*	131,299*	128,983*	129,167*	131,242*	129,570*	129,074*
	(0.021)	(0.019)	(0.022)	(0.02)	(0.021)	(0.021)	(0.021)	(0.021)
Skewness	8.86*	8.39*	9.07*	8.81*	8.85*	9.06*	8.88*	8.84*
	(0.021)	(0.019)	(0.022)	(0.02)	(0.021)	(0.021)	(0.021)	(0.021)
WHEAT								
Mean	90,402***	90,715***	90,404***	90,464***	90,306***	90,437***	90,289***	90,314***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	133,218**	133,765**	133,195**	133,389**	133,271**	133,223**	133,169**	133,280**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Skewness	3.76**	3.87**	3.75**	3.79**	3.76**	3.77**	3.75**	3.76**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Note: 1) Estimated output distribution moments with p-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Outputs of all crops are in thousand bushels, except cotton which is in thousand lbs.

Table 20: Output distribution moments under ENSO (El Niño)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	367,580***	366,832***	367,244***	367,727***	367,589***	367,241***	367,371***	367,616***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	664,926	652,833	669,611	665,264	667,530	668,457	666,382	667,591
	(0.059)	(0.056)	(0.06)	(0.059)	(0.059)	(0.06)	(0.059)	(0.059)
Skewness	18.82	18.17	19.15	18.83	18.98	19.08	18.93	18.98
	(0.059)	(0.056)	(0.06)	(0.059)	(0.059)	(0.06)	(0.059)	(0.059)
COTTON								
Mean	792,586**	799,451**	787,923**	791,191**	791,965**	789,694**	789,755**	791,956**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Standard deviation	922,521	920,091	920,868	921,947	920,779	917,694	926,246	921,059
	(0.069)	(0.07)	(0.067)	(0.069)	(0.069)	(0.069)	(0.065)	(0.069)
Skewness	4.2	4.23	4.13	4.21	4.19	4.19	4.1	4.19
	(0.069)	(0.07)	(0.067)	(0.069)	(0.069)	(0.069)	(0.065)	(0.069)
SORGHUM								
Mean	71,694***	71,565***	71,691***	71,578***	77,119***	71,689***	71,695***	71,698***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	79,112***	79,084***	79,111***	78,967***	80,163***	79,111***	79,112***	79,112**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.007)
Skewness	1.19***	1.19***	1.19***	1.19***	1.09***	1.19***	1.19***	1.19**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.007)
SOYBEANS								
Mean	107,463***	107,095***	107,526***	107,486***	107,358***	107,461***	107,437***	107,360***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	124,633*	120,550*	126,140*	123,767*	124,262*	124,951*	124,762*	124,271*
	(0.02)	(0.018)	(0.02)	(0.019)	(0.02)	(0.02)	(0.02)	(0.02)
Skewness	8.08*	7.69*	8.24*	7.98*	8.05*	8.12*	8.1*	8.05*
	(0.02)	(0.018)	(0.02)	(0.019)	(0.02)	(0.02)	(0.02)	(0.02)
WHEAT								
Mean	91,108***	91,673***	91,117***	91,328***	91,301***	91,446***	91,069***	91,309***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	133,413**	133,945**	133,392**	133,638**	133,603**	133,552**	133,415**	133,612**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Skewness	3.74**	3.8**	3.7**	3.76**	3.73**	3.74**	3.72**	3.73**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Note: 1) Estimated output distribution moments with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Outputs of all crops are in thousand bushels, except cotton which is in thousand lbs.

Table 21: Output distribution moments under ENSO (La Niña)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	365,392***	364,360***	365,078***	365,509***	365,350***	365,156***	365,182***	365,382***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	660,211	644,497	665,112	660,196	662,169	664,965	661,578	662,281
	(0.059)	(0.056)	(0.06)	(0.059)	(0.06)	(0.06)	(0.06)	(0.06)
Skewness	18.78	17.95	19.12	18.77	18.91	19.1	18.89	18.91
	(0.059)	(0.056)	(0.06)	(0.059)	(0.06)	(0.06)	(0.06)	(0.06)
COTTON								
Mean	783,326**	790,916**	778,750**	781,923**	782,701**	780,476**	780,579**	782,692**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Standard deviation	912,627	907,678	910,776	912,023	910,868	907,807	915,950	911,149
	(0.069)	(0.071)	(0.067)	(0.069)	(0.069)	(0.069)	(0.065)	(0.069)
Skewness	4.24	4.32	4.16	4.24	4.22	4.23	4.13	4.23
	(0.069)	(0.071)	(0.067)	(0.069)	(0.069)	(0.069)	(0.065)	(0.069)
SORGHUM								
Mean	72,821	72,112***	71,751***	77,173	71,761***	71,742***	71,745***	71,757***
	(0.825)	(<0.001)	(<0.001)	(0.819)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	79,388	79,236**	79,165***	80,210	79,161***	79,157***	79,158***	79,160***
	(0.851)	(0.002)	(<0.001)	(0.846)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.17	1.18**	1.19***	1.09	1.19***	1.19***	1.19***	1.19***
	(0.851)	(0.002)	(<0.001)	(0.846)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	106,832***	106,418***	106,852***	106,881***	106,728***	106,873***	106,775***	106,734***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	123,803*	118,897*	124,632*	123,342*	123,473*	124,698*	123,419*	123,537*
	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Skewness	8.08*	7.61*	8.16*	8.03*	8.06*	8.17*	8.04*	8.06*
	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
WHEAT								
Mean	90,462***	91,044***	90,787***	90,825***	90,683***	91,044***	90,673***	90,690***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	133,082**	133,654**	133,263**	133,422**	133,330**	133,399**	133,250**	133,340**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Skewness	3.71**	3.82**	3.74**	3.78**	3.76**	3.77**	3.75**	3.76**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Note: 1) Estimated output distribution moments with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2) Outputs of all crops are in thousand bushels, except cotton which is in thousand lbs.

Table 22: Revenue distribution moments estimated with log skew-normal

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	883,105***	893,958***	878,800***	883,819***	883,761***	881,903***	883,065***	882,791***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	3,245,402	3,407,697	3,263,973	3,239,447	3,248,370	3,252,408	3,248,497	3,278,811
	(0.13)	(0.17)	(0.135)	(0.129)	(0.13)	(0.131)	(0.13)	(0.134)
Skewness	105.79	117.74	109.16	105	105.83	106.87	106.1	109.04
	(0.13)	(0.17)	(0.135)	(0.129)	(0.13)	(0.131)	(0.13)	(0.134)
COTTON								
Mean	34,255**	34,315**	34,036**	34,230**	34,196**	34,098**	34,106**	34,198**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Standard deviation	68,059	68,697	67,727	68,124	67,924	67,597	67,153	67,963
	(0.093)	(0.093)	(0.095)	(0.093)	(0.093)	(0.093)	(0.092)	(0.093)
Skewness	12.7	13.33	12.61	12.75	12.69	12.64	12.05	12.71
	(0.093)	(0.093)	(0.095)	(0.093)	(0.093)	(0.093)	(0.092)	(0.093)
SORGHUM								
Mean	236,320***	238,136***	228,303***	235,930***	235,444***	242,643***	235,874***	220,781***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	297,574***	298,152***	289,136***	297,448***	295,922***	299,551***	296,549***	273,388***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.43***	1.42***	1.44***	1.43***	1.43***	1.39***	1.43***	1.41***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	501,355***	505,091***	500,508***	501,483***	501,179***	501,737***	501,721***	502,767***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	948,223**	988,929**	963,639**	940,047**	944,653**	952,231**	952,668**	970,150**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Skewness	17.83**	19.82**	18.78**	17.42**	17.67**	18**	18.04**	18.78**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
WHEAT								
Mean	262,075***	296,749**	265,433***	275,863**	271,737**	271,372**	267,941***	272,183**
	(<0.001)	(0.003)	(<0.001)	(0.003)	(0.002)	(0.003)	(<0.001)	(0.002)
Standard deviation	737,647	1,181,795	780,603	892,492	844,395	839,306	802,951	847,676
	(0.266)	(0.388)	(0.349)	(0.406)	(0.399)	(0.405)	(0.348)	(0.397)
Skewness	20.35	61.56	23.34	31.4	27.58	27.35	24.67	27.77
	(0.266)	(0.388)	(0.349)	(0.406)	(0.399)	(0.405)	(0.348)	(0.397)

Note: 1) Estimated crop revenue distribution moments with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Revenues of all crops are in million dollars.

Table 23: Revenue distribution moments under ENSO (Neutral)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	927,245***	949,848***	923,156***	928,406***	928,034***	926,794***	927,579***	928,665***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	3,517,668	3,862,493	3,542,875	3,518,137	3,523,085	3,538,598	3,527,183	3,527,436
	(0.124)	(0.21)	(0.127)	(0.123)	(0.124)	(0.125)	(0.124)	(0.124)
Skewness	115.48	141.42	119.49	115.12	115.69	117.63	116.26	115.87
	(0.124)	(0.21)	(0.127)	(0.123)	(0.124)	(0.125)	(0.124)	(0.124)
COTTON								
Mean	35,653**	36,041**	35,385**	35,622**	35,590**	35,497**	35,488**	35,592**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Standard deviation	67,457	68,953	66,958	67,484	67,295	67,019	66,980	67,333
	(0.082)	(0.082)	(0.083)	(0.082)	(0.082)	(0.082)	(0.081)	(0.082)
Skewness	9.95	10.89	9.89	9.97	9.93	9.9	9.73	9.94
	(0.082)	(0.082)	(0.083)	(0.082)	(0.082)	(0.082)	(0.081)	(0.082)
SORGHUM								
Mean	248,967***	248,868***	244,847***	245,861***	248,621***	250,494***	248,225***	249,546***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	308,876***	308,845***	305,167***	307,905***	308,769***	311,489***	308,646***	309,054***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.4***	1.4***	1.41***	1.42***	1.4***	1.4***	1.4***	1.4***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	497,068***	501,449***	496,313***	497,199***	496,877***	497,745***	497,504***	496,932***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	941,330**	989,529**	957,437**	933,164**	937,755**	948,742**	946,690**	937,141**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Skewness	17.67**	20.06**	18.65**	17.26**	17.51**	17.99**	17.92**	17.47**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
WHEAT								
Mean	264,936***	287,469**	262,412***	268,185***	265,241***	264,545***	263,304***	265,383***
	(<0.001)	(0.004)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	725,637	1,006,755	701,205	760,304	727,926	719,803	704,922	728,790
	(0.226)	(0.424)	(0.213)	(0.267)	(0.243)	(0.245)	(0.202)	(0.243)
Skewness	18.5	39.49	17.17	20.53	18.53	18.15	17.22	18.56
	(0.226)	(0.424)	(0.213)	(0.267)	(0.243)	(0.245)	(0.202)	(0.243)

Note: 1) Estimated crop revenue distribution moments with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Revenues of all crops are in million dollars.

Table 24: Revenue distribution moments under ENSO (El Niño)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	906,734***	919,152***	902,458***	907,758***	907,367***	905,727***	906,616***	907,988***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	3,339,115	3,525,285	3,359,373	3,337,735	3,342,482	3,349,883	3,341,969	3,346,685
	(0.126)	(0.167)	(0.13)	(0.125)	(0.125)	(0.127)	(0.126)	(0.126)
Skewness	106.34	119.76	109.78	105.88	106.42	107.67	106.64	106.59
	(0.126)	(0.167)	(0.13)	(0.125)	(0.125)	(0.127)	(0.126)	(0.126)
COTTON								
Mean	35,242**	35,441**	34,985**	35,213**	35,180**	35,083**	35,090**	35,181**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Standard deviation	66,823	68,285	66,367	66,851	66,665	66,373	66,318	66,699
	(0.085)	(0.086)	(0.086)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
Skewness	10.42	11.41	10.35	10.44	10.4	10.36	10.14	10.41
	(0.085)	(0.086)	(0.086)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
SORGHUM								
Mean	239,299***	230,433***	228,493***	238,730***	239,350***	239,392***	241,327***	239,360***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Standard deviation	298,518***	295,638***	289,198***	298,340***	298,534***	298,547***	299,148***	298,537***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Skewness	1.41***	1.46***	1.44***	1.41***	1.41***	1.41***	1.4***	1.41***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
SOYBEANS								
Mean	504,910***	508,706***	504,044***	505,056***	504,730***	505,291***	505,265***	504,780***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	954,088**	995,739**	969,480**	946,105**	950,576**	958,199**	958,530**	949,914**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Skewness	17.71**	19.74**	18.65**	17.32**	17.55**	17.89**	17.91**	17.51**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
WHEAT								
Mean	269,044***	291,537**	263,155***	272,017**	269,057***	268,428***	266,534***	269,244***
	(<0.001)	(0.007)	(<0.001)	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	788,400	1,061,979	722,265	814,250	777,528	769,598	754,680	778,982
	(0.348)	(0.461)	(0.279)	(0.37)	(0.346)	(0.348)	(0.307)	(0.346)
Skewness	22.8	45.14	18.72	24.38	21.87	21.47	20.53	21.94
	(0.348)	(0.461)	(0.279)	(0.37)	(0.346)	(0.348)	(0.307)	(0.346)

Note: 1) Estimated crop revenue distribution moments with *p*-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Revenues of all crops are in million dollars.

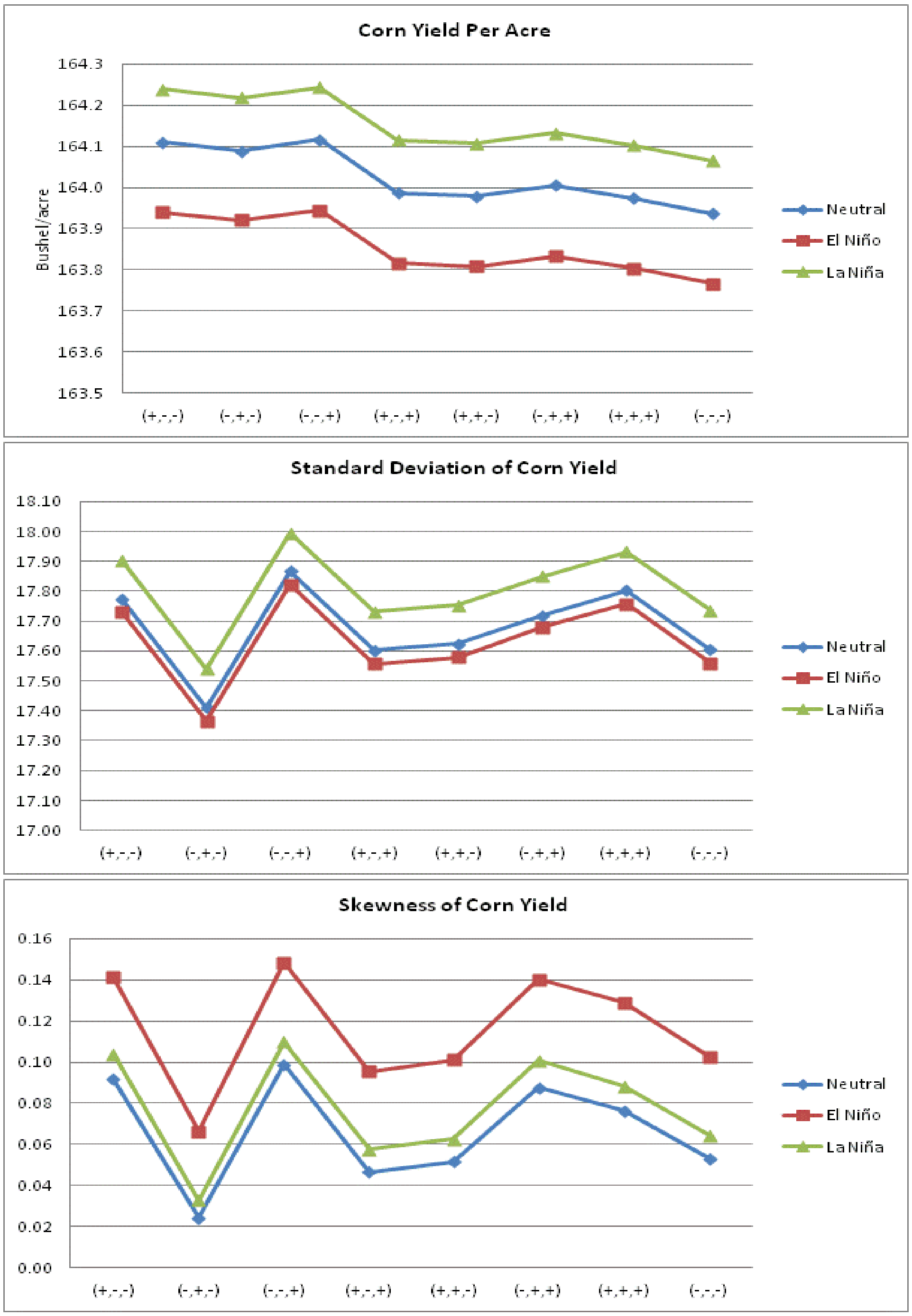
Table 25: Revenue distribution moments under ENSO (La Niña)

	(PDO+, TAG-, WPWP-)	(PDO-, TAG+, WPWP-)	(PDO-, TAG-, WPWP+)	(PDO+, TAG-, WPWP+)	(PDO+, TAG+, WPWP-)	(PDO-, TAG+, WPWP+)	(PDO+, TAG+, WPWP+)	(PDO+, TAG-, WPWP-)
CORN								
Mean	890,990***	909,519**	886,971***	891,644***	891,677***	890,092***	891,223***	892,352***
	(<0.001)	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	3,362,190	3,641,350	3,386,026	3,355,132	3,365,650	3,374,718	3,369,451	3,370,736
	(0.139)	(0.241)	(0.145)	(0.137)	(0.139)	(0.141)	(0.14)	(0.14)
Skewness	113.99	135.44	117.96	113.08	114.06	115.55	114.62	114.3
	(0.139)	(0.241)	(0.145)	(0.137)	(0.139)	(0.141)	(0.14)	(0.14)
COTTON								
Mean	33,969**	34,284**	33,719**	33,941**	33,909**	33,816**	33,822**	33,910**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Standard deviation	64,693	67,722	64,250	64,732	64,557	64,272	64,208	64,589
	(0.083)	(0.089)	(0.085)	(0.083)	(0.083)	(0.084)	(0.083)	(0.083)
Skewness	10.46	12.51	10.4	10.5	10.45	10.42	10.18	10.47
	(0.083)	(0.089)	(0.085)	(0.083)	(0.083)	(0.084)	(0.083)	(0.083)
SORGHUM								
Mean	233,820***	235,798***	233,427***	243,005***	239,955***	239,469***	239,075***	242,960**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)

Standard deviation	296,935***	297,579***	296,806***	299,838***	298,899	303,207***	298,623***	299,824**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)
Skewness	1.45***	1.43***	1.45***	1.39***	1.41	1.44***	1.41***	1.39**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)
SOYBEANS								
Mean	495,098***	499,184***	494,325***	495,210***	494,914***	495,680***	495,531***	494,970***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	938,618**	983,171**	954,529**	930,238**	934,965**	944,772**	943,729**	934,362**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Skewness	17.9**	20.1**	18.88**	17.48**	17.73**	18.17**	18.13**	17.69**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
WHEAT								
Mean	257,511***	281,443**	261,128***	267,857**	264,722***	264,481***	262,079***	264,875***
	(<0.001)	(0.004)	(<0.001)	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Standard deviation	711,713	1,002,862	754,311	825,662	790,457	780,801	759,148	791,468
	(0.238)	(0.416)	(0.324)	(0.372)	(0.359)	(0.355)	(0.306)	(0.359)
Skewness	18.91	41.72	21.75	26.49	23.94	23.33	21.88	23.99
	(0.238)	(0.416)	(0.324)	(0.372)	(0.359)	(0.355)	(0.306)	(0.359)

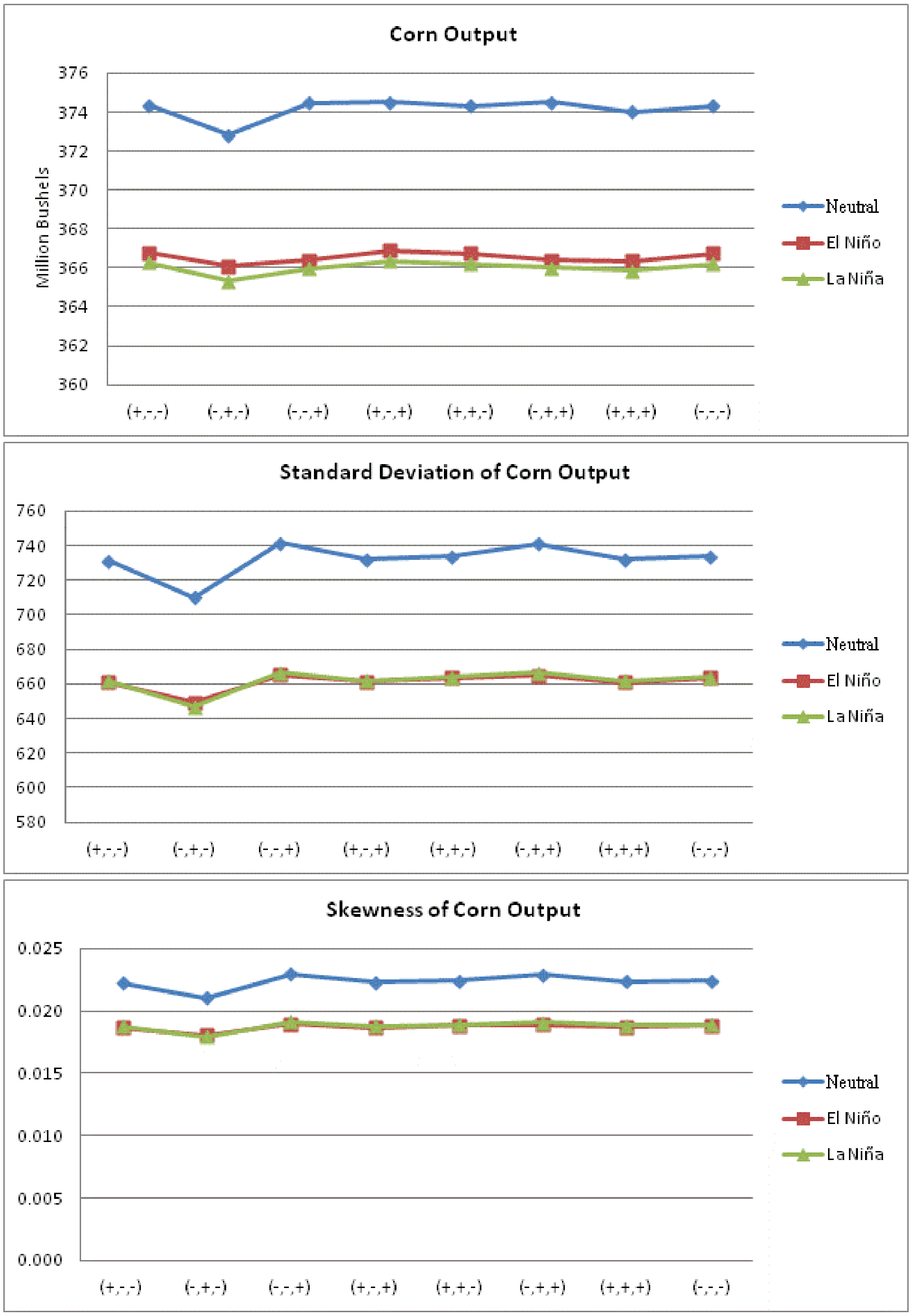
Note: 1) Estimated crop revenue distribution moments with p-values in parentheses; with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) Revenues of all crops are in million dollars.

Figure 8: Fitted yield moments for DCV and ENSO phases: Corn



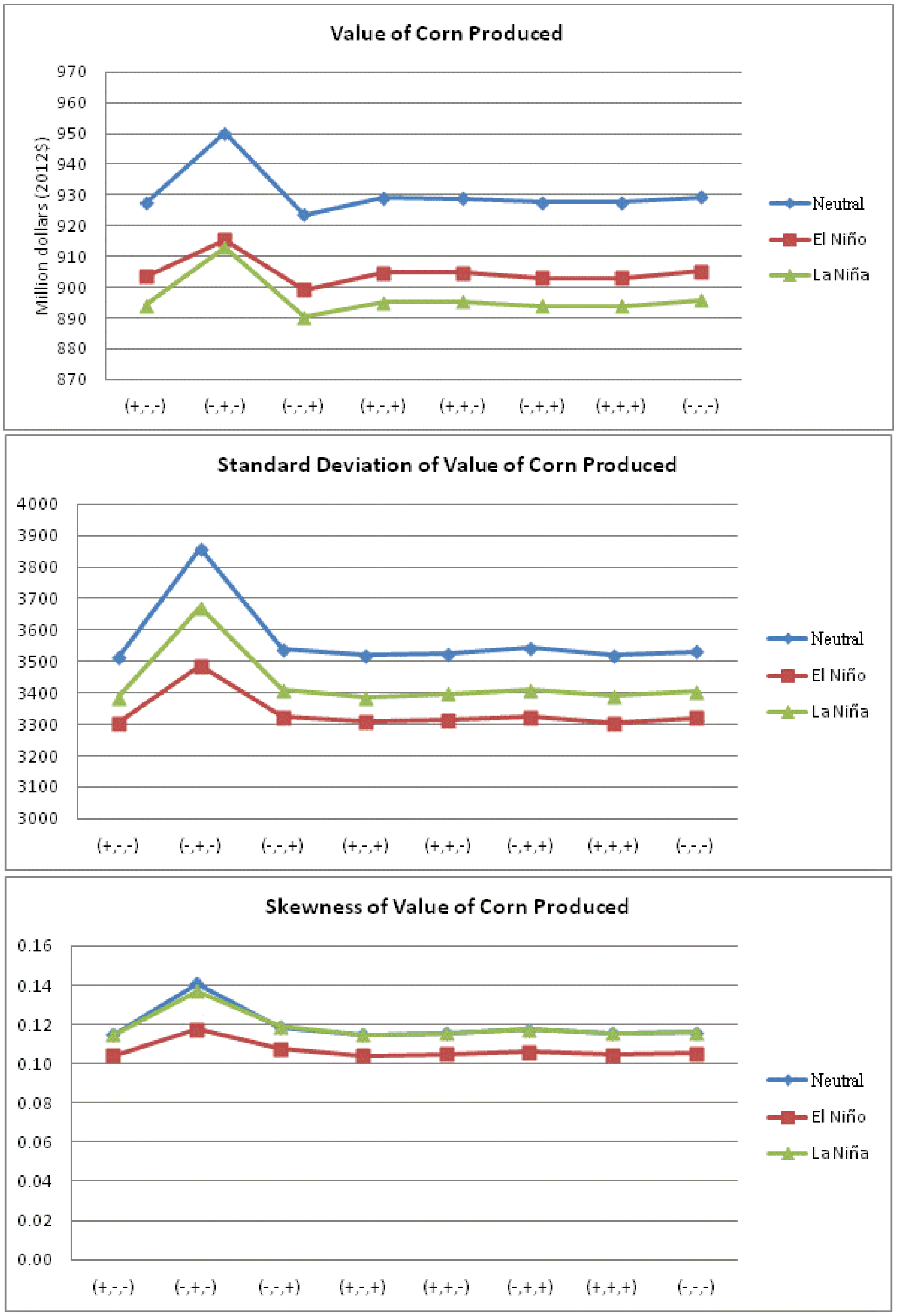
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 9: Fitted output moments in DCV and ENSO phases: Corn



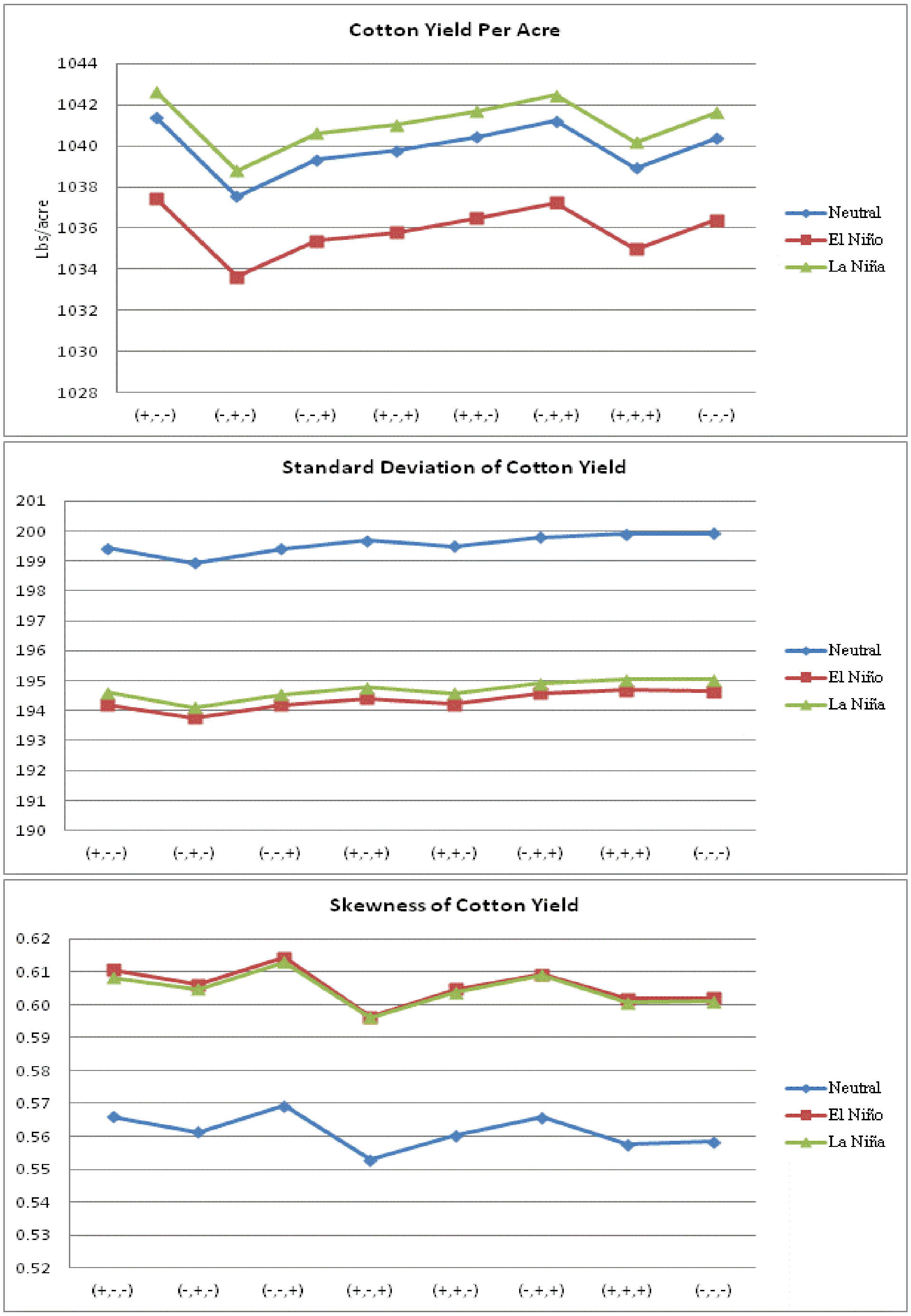
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 10: Fitted revenue moments in DCV and ENSO phases: Corn



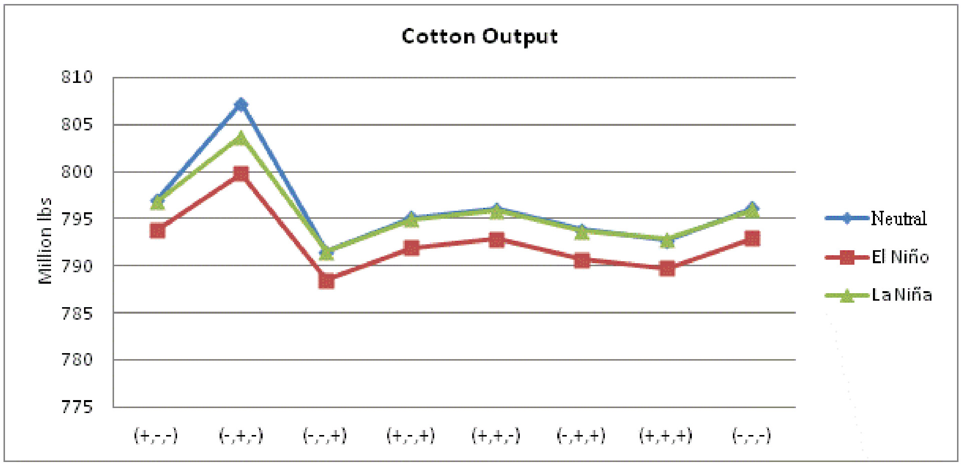
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

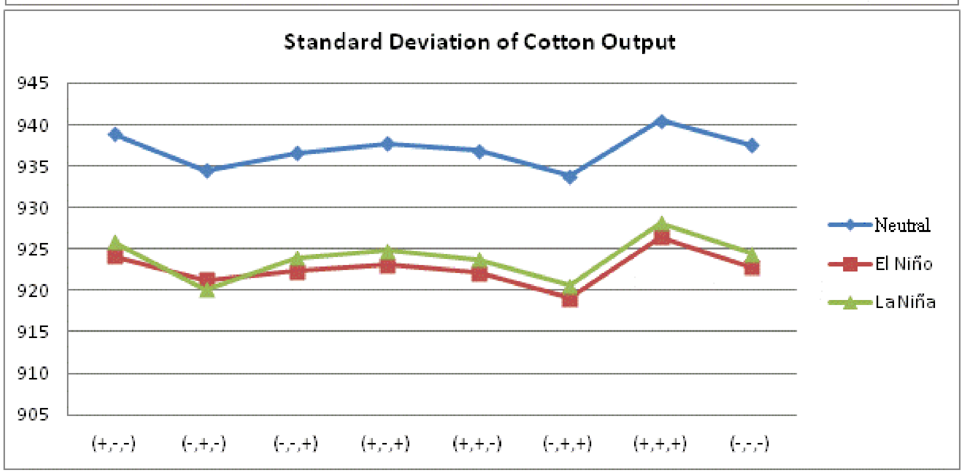
Figure 11: Fitted yield moments in DCV and ENSO phases: Cotton

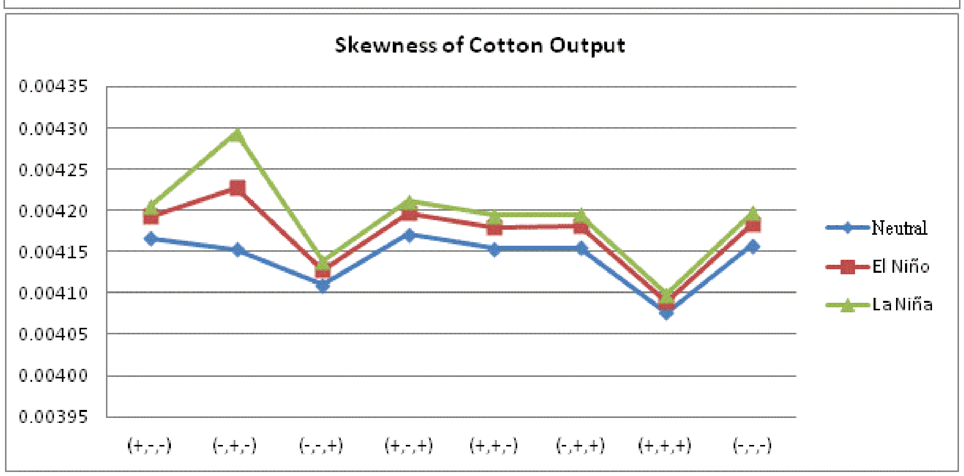


Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 12: Fitted output moments in DCV and ENSO phases: Cotton

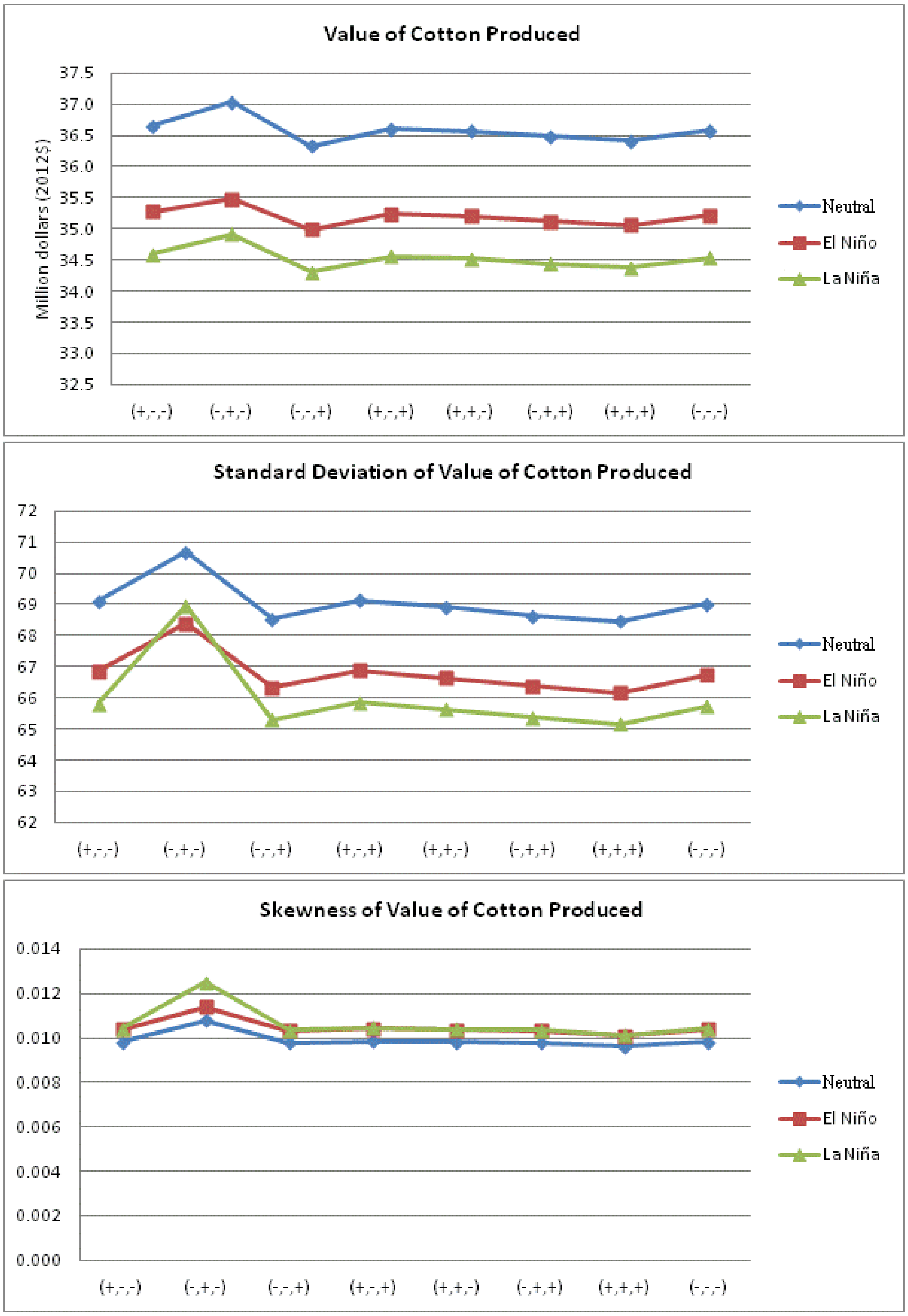






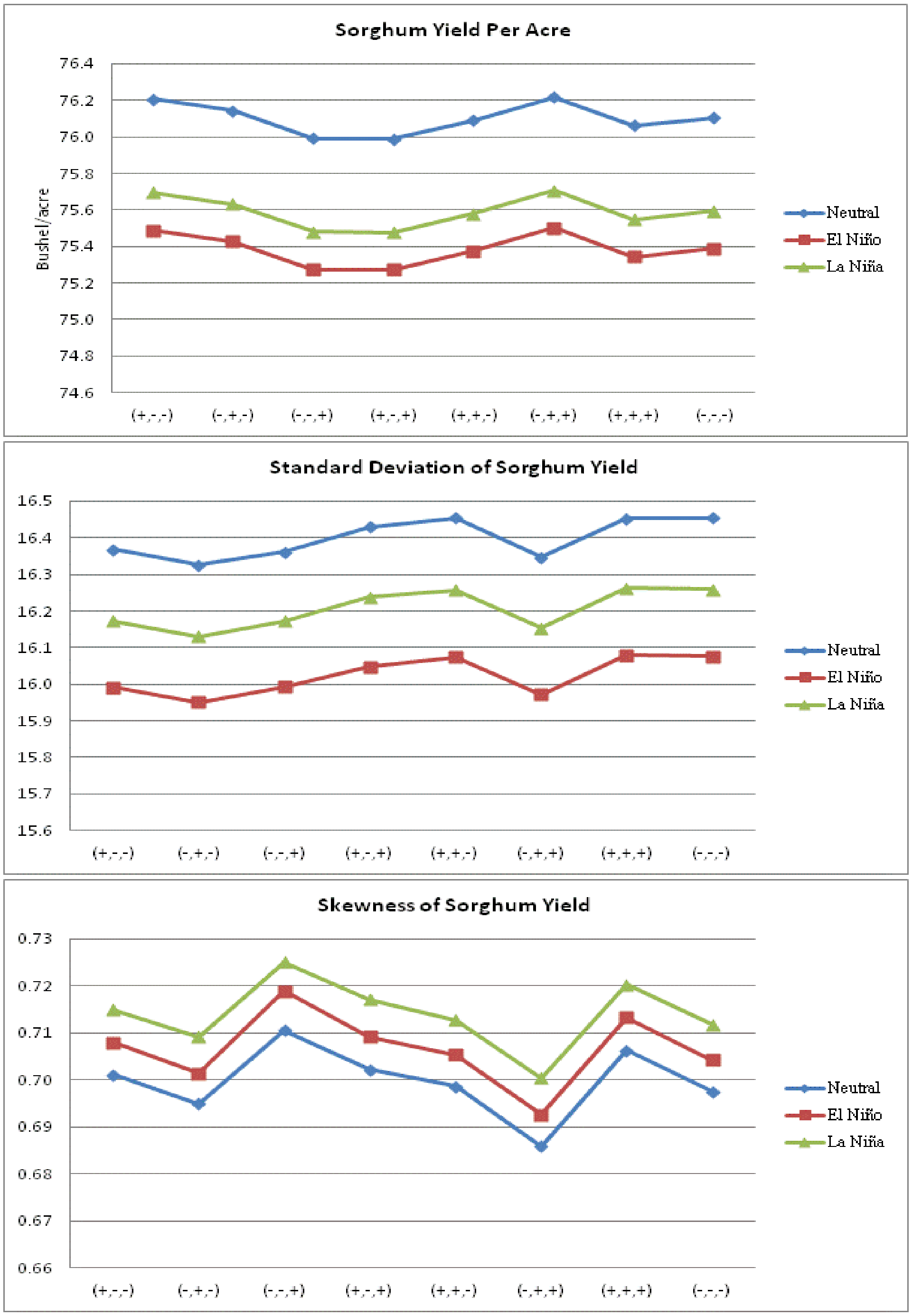
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 13: Fitted revenue moments in DCV and ENSO phases: Cotton



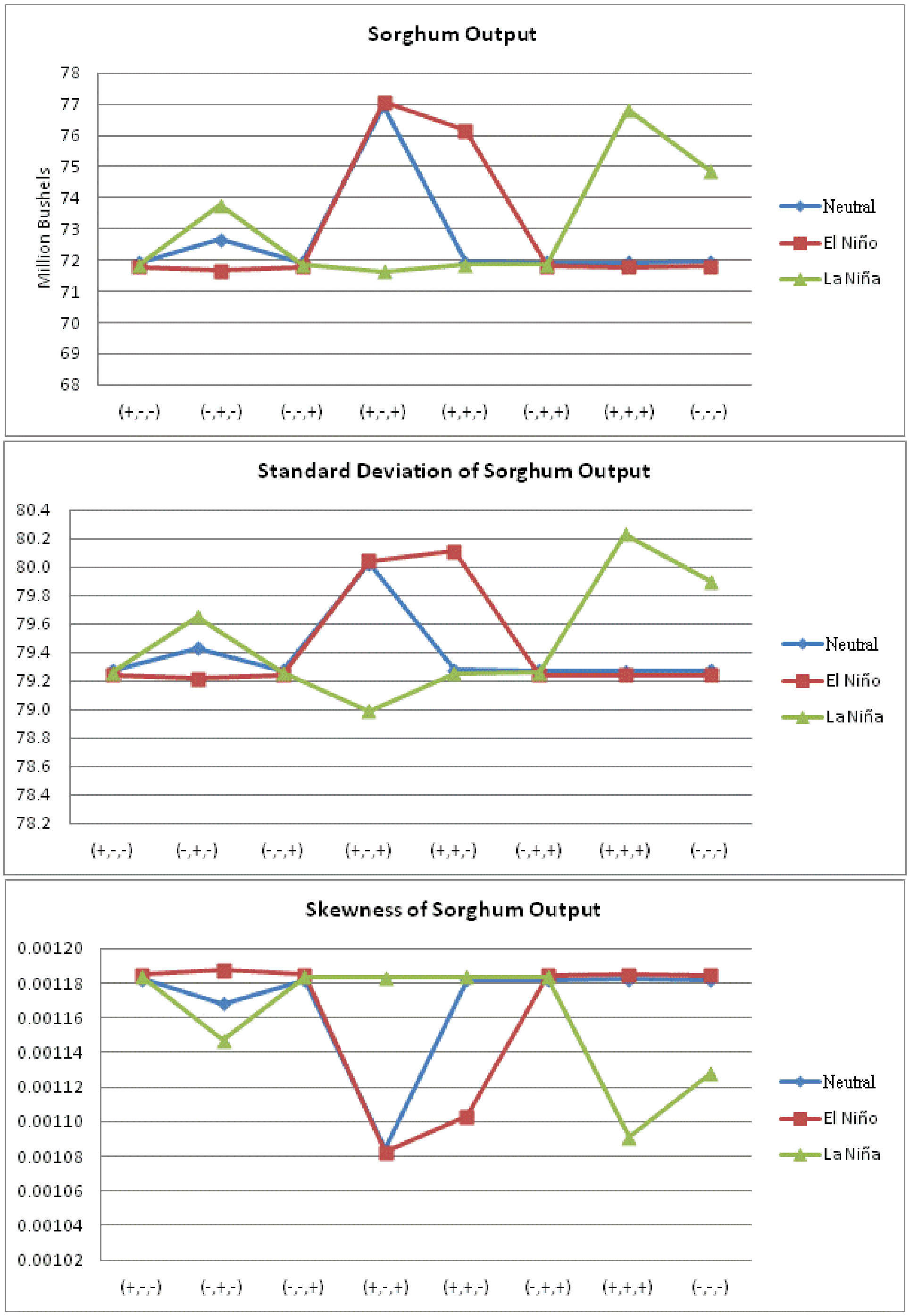
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 14: Fitted yield moments in DCV and ENSO phases: Sorghum



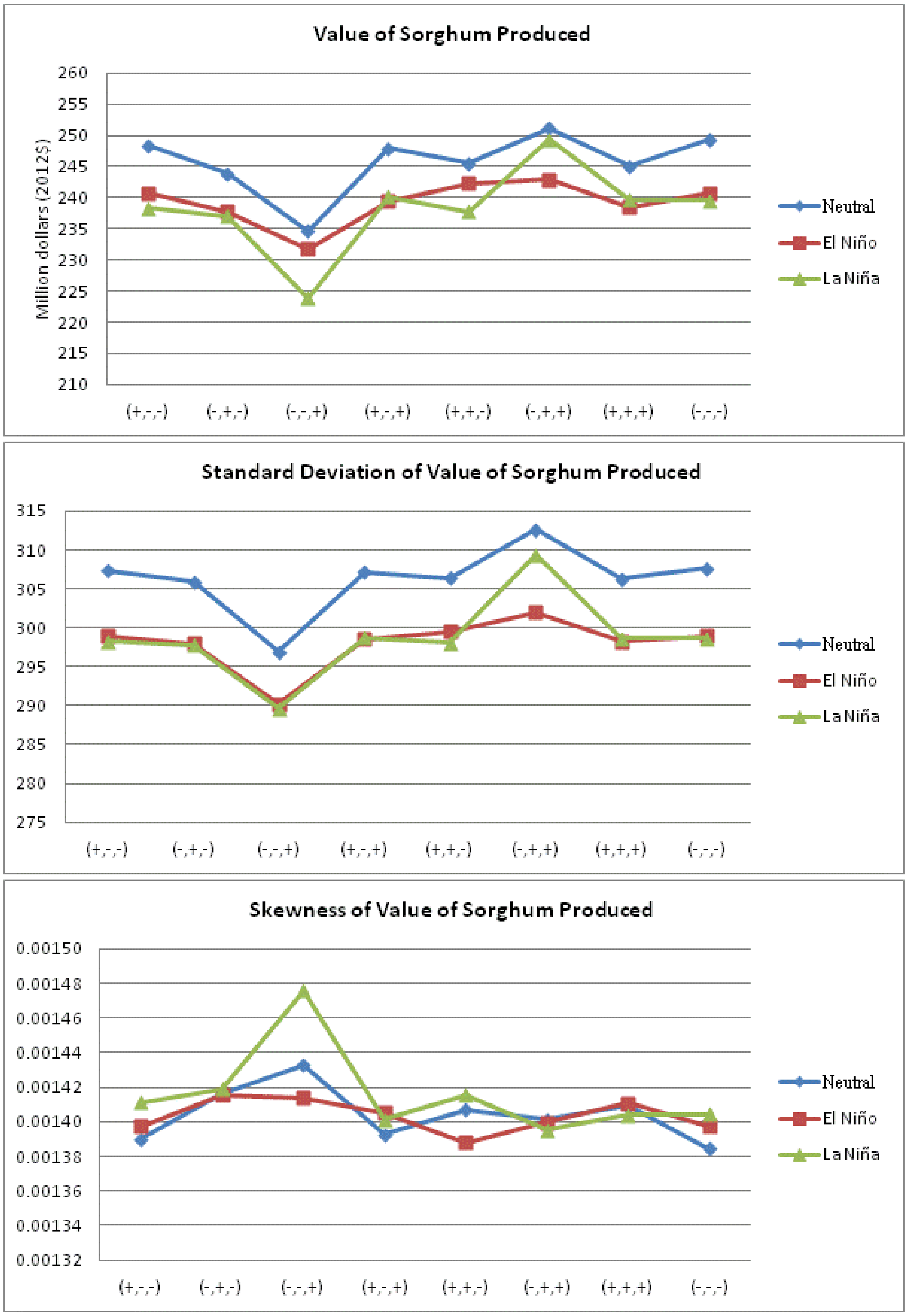
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 15: Fitted output moments in DCV and ENSO phases: Sorghum



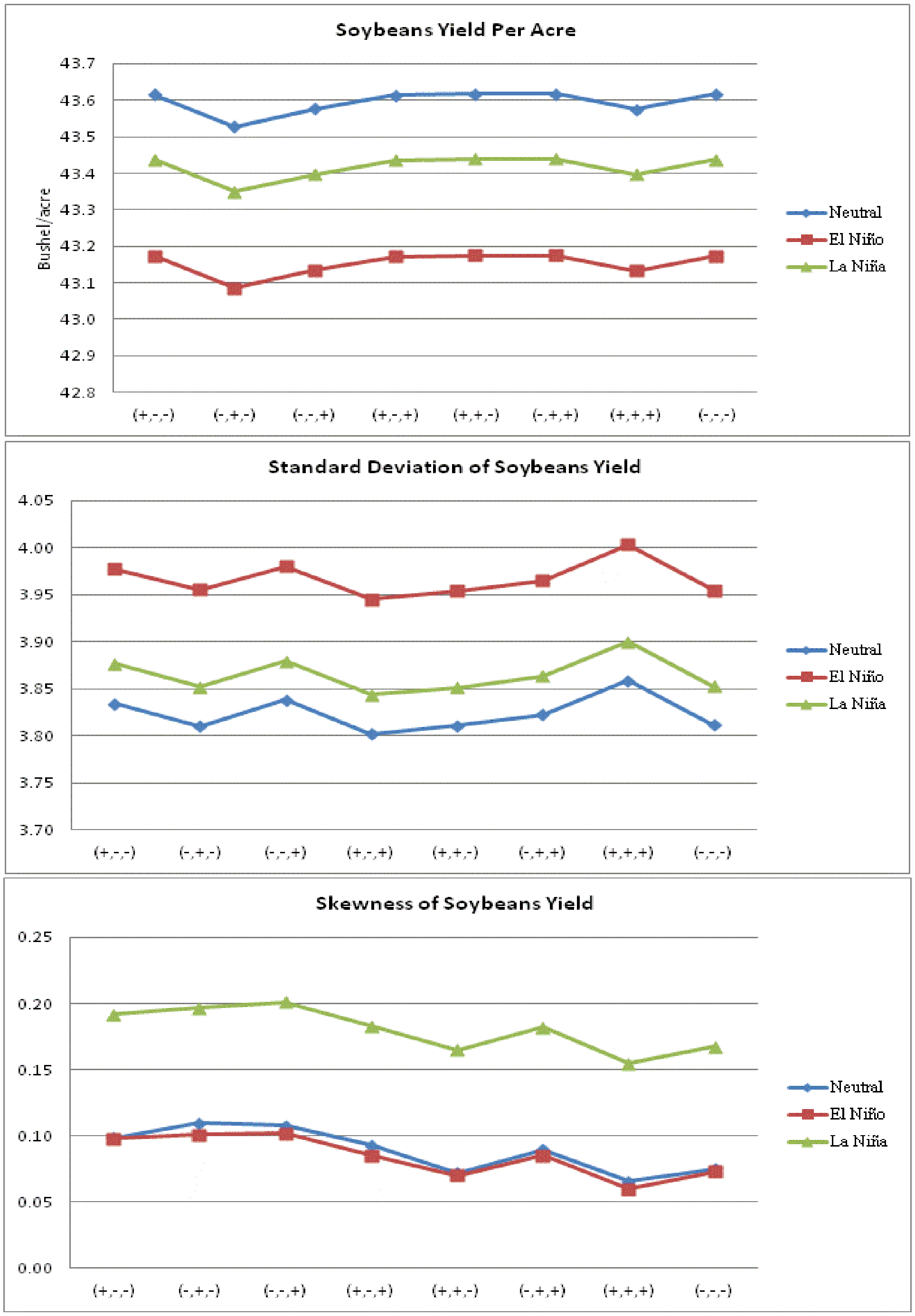
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 16: Fitted revenue moments in DCV and ENSO phases: Sorghum



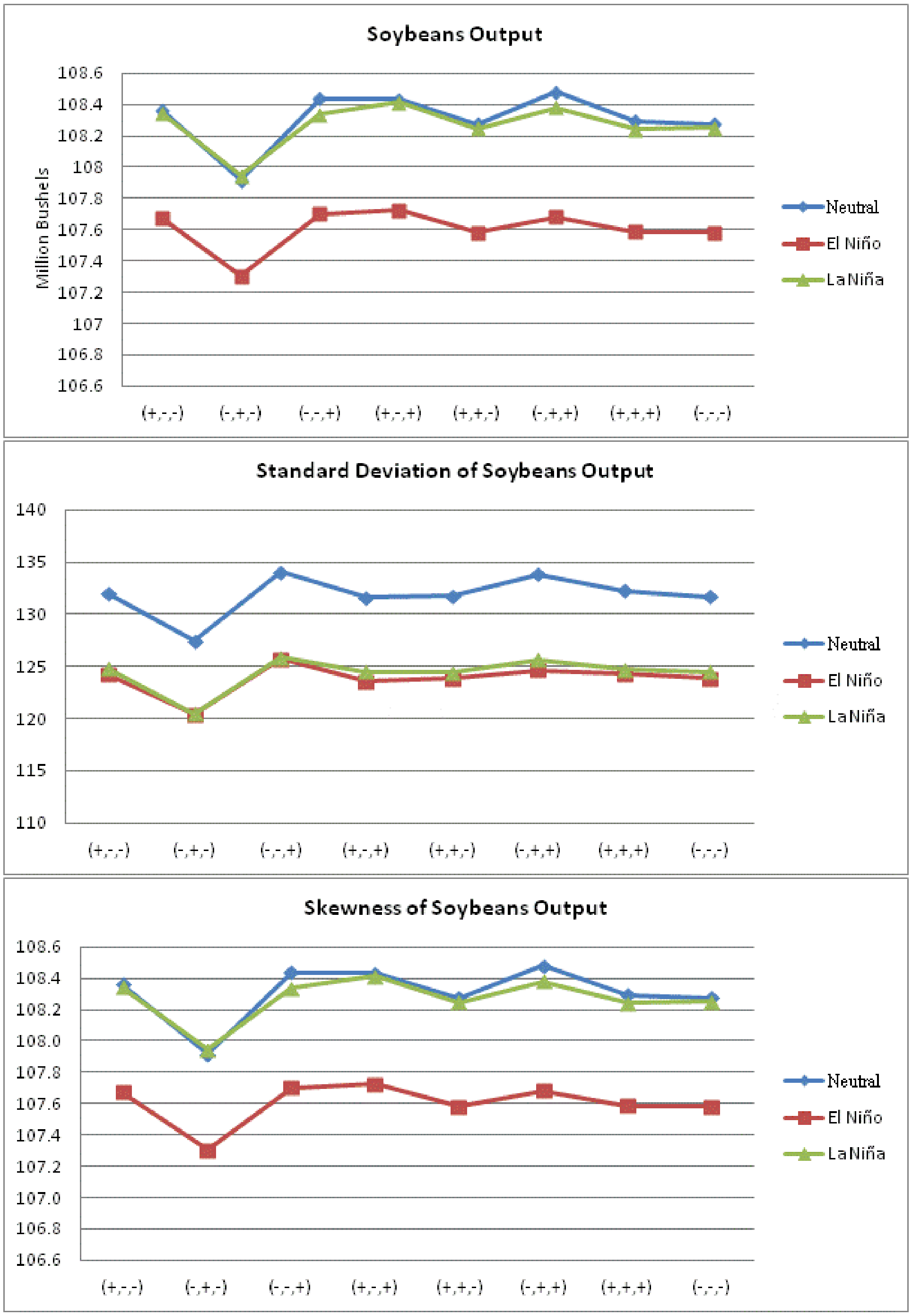
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 17: Fitted yield moments in DCV and ENSO phases: Soybeans



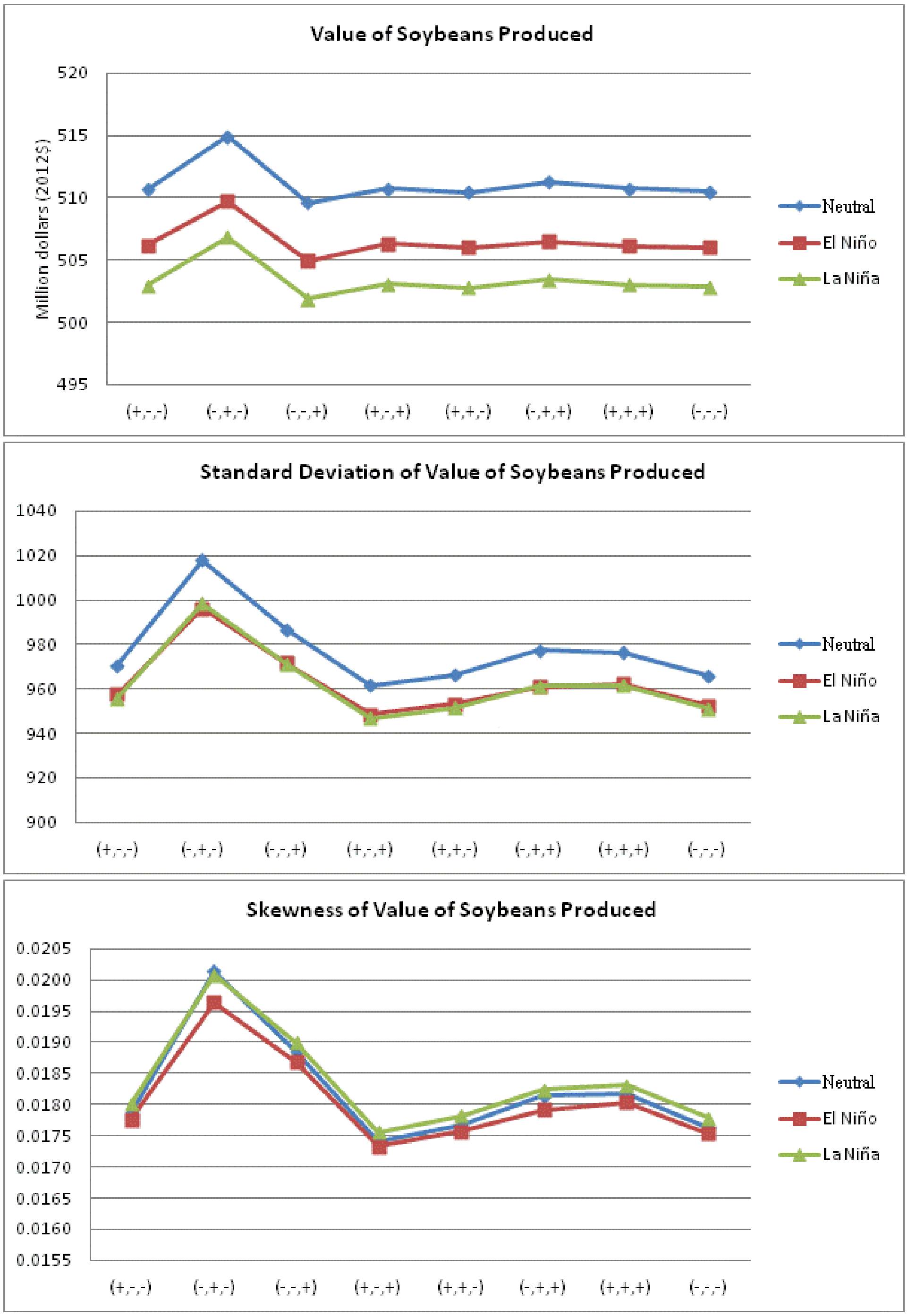
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 18: Fitted output moments in DCV and ENSO phases: Soybeans



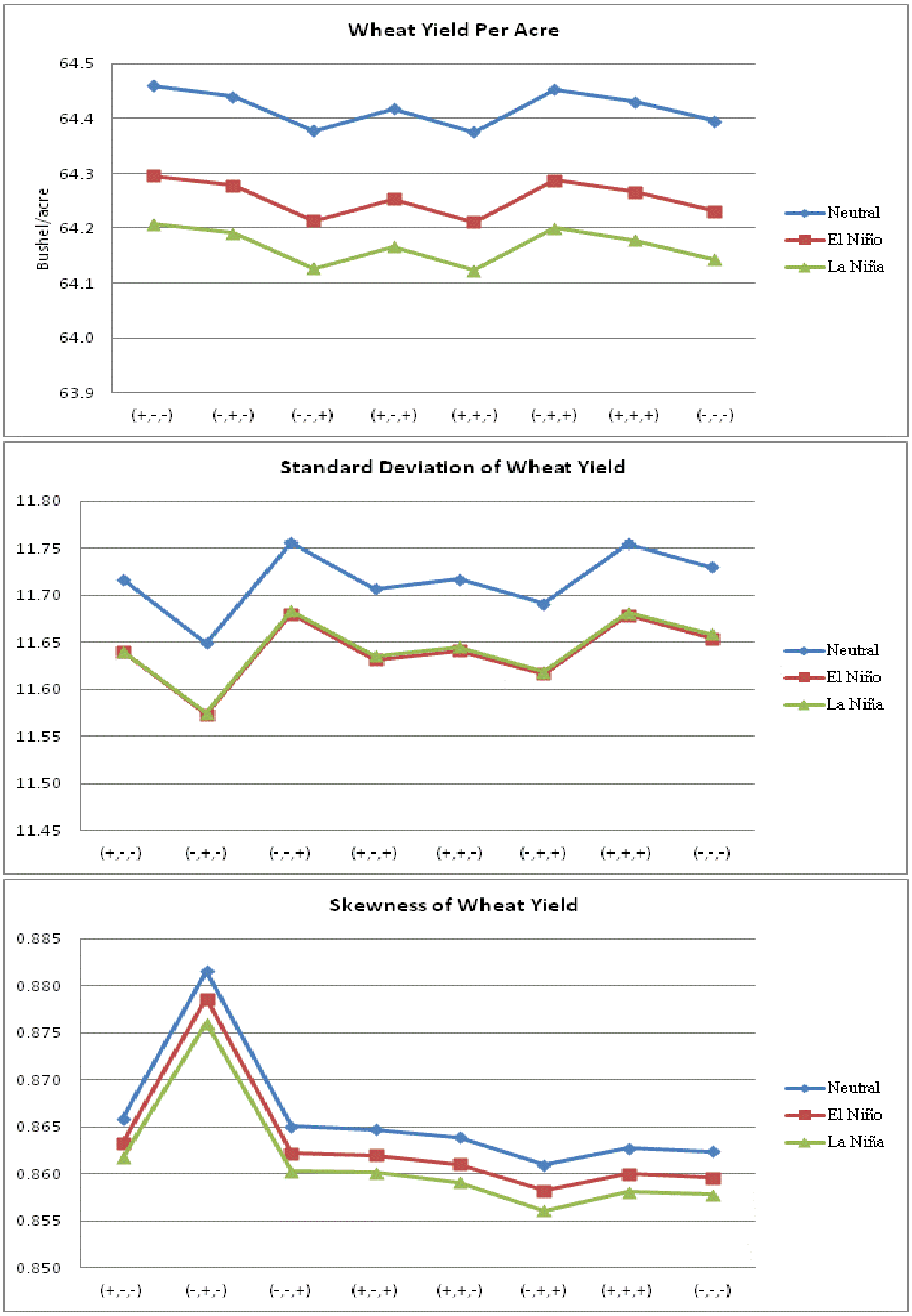
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 19: Fitted revenue moments in DCV and ENSO phases: Soybeans



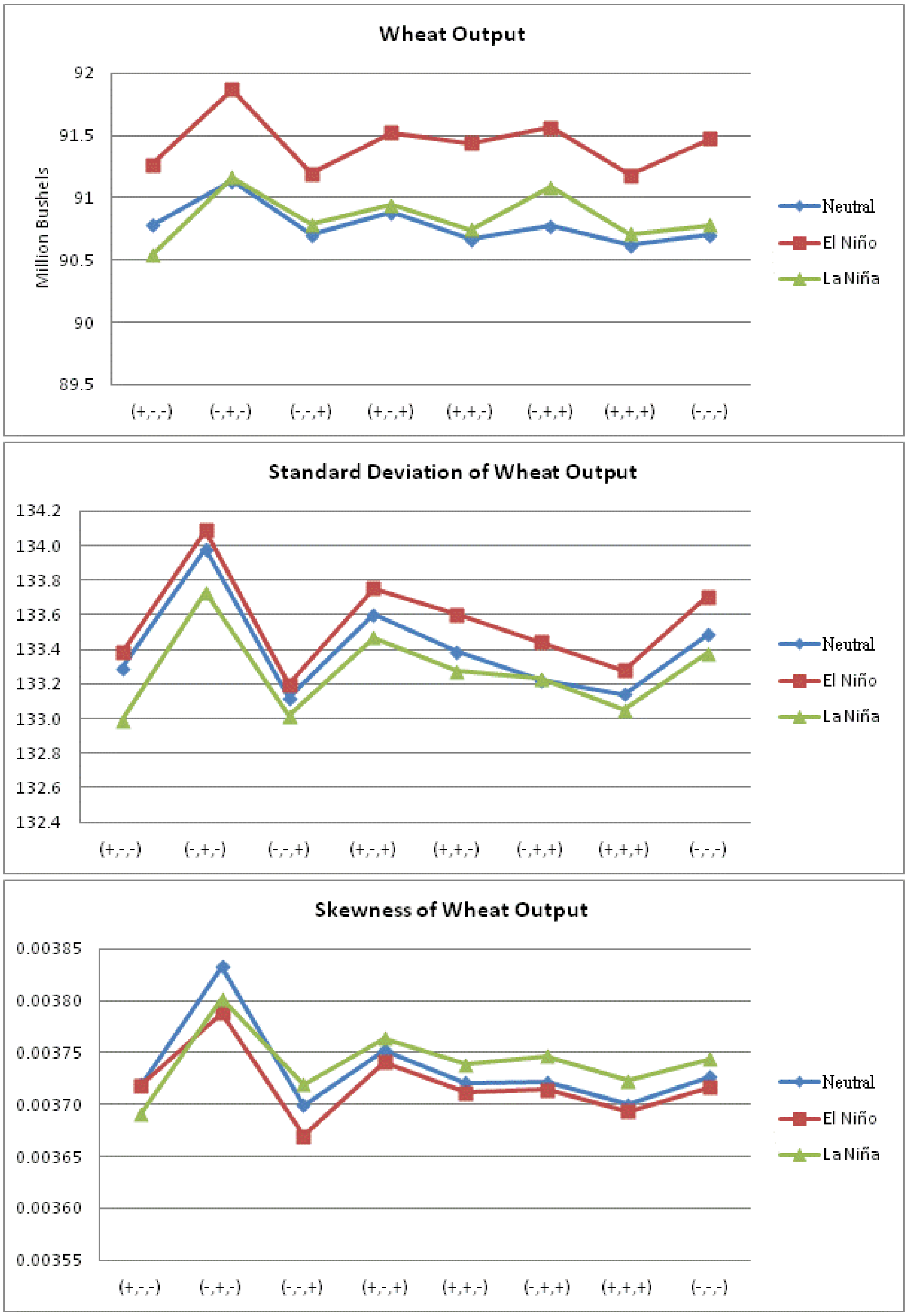
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 20: Fitted yield moments in DCV and ENSO phases: Wheat



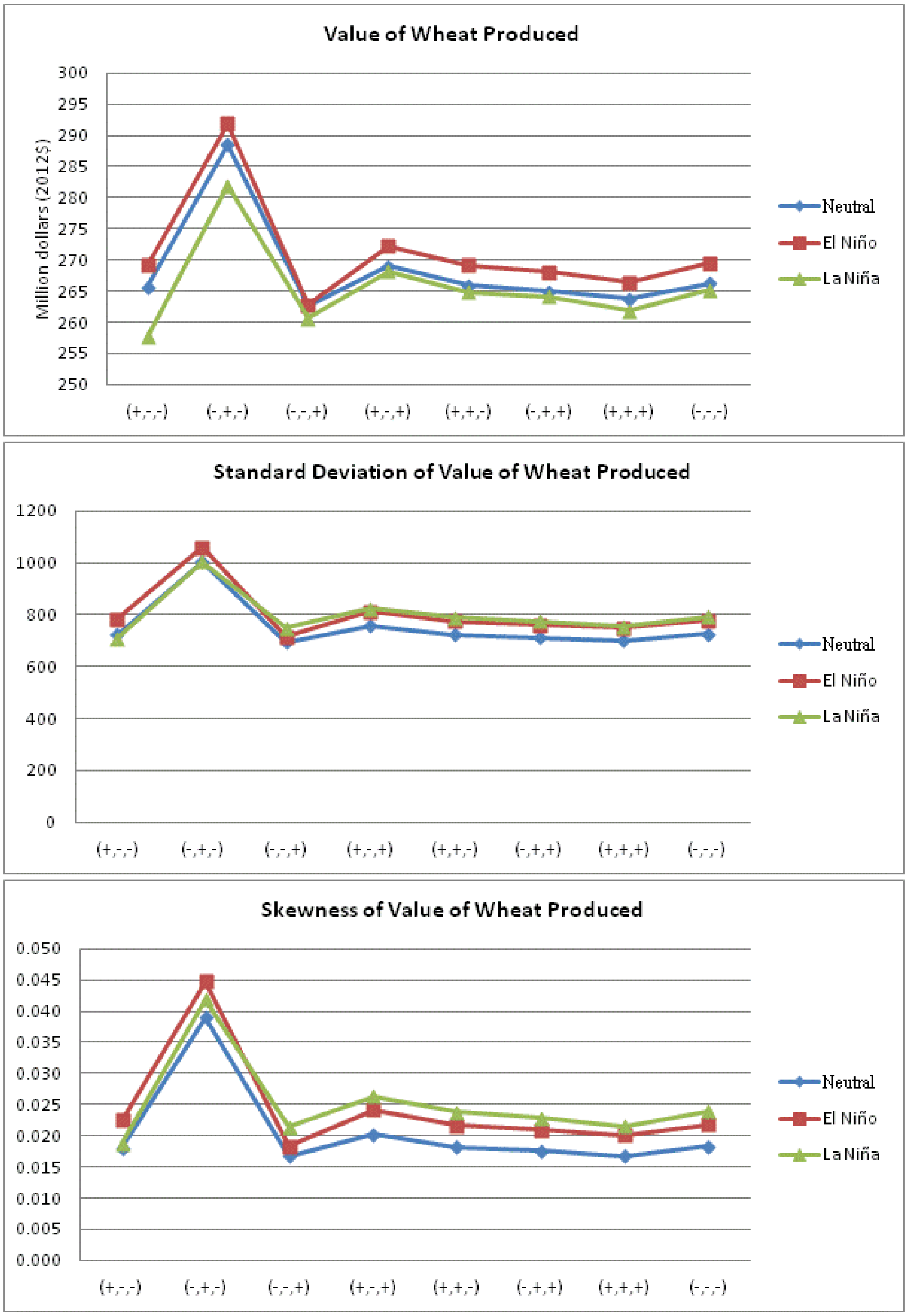
Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 21: Fitted output moments in DCV and ENSO phases: Wheat



Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Figure 22: Fitted revenue moments in DCV and ENSO phases: Wheat



Note: The distribution moments are evaluated for different DCV and ENSO phase combinations (time fixed at 2012). The DCV combinations of (PDO, TAG, WPWP) are identified on the horizontal axis.

Table 26: Scenario-based averages from DCV and ENSO adapted agriculture

	Revenue ($ millions)	Harvested (Thousand Acreages)	Cost ($ millions)	Profit ($ millions)	Net profit margin
Corn	32,826,819.1	2,143.1	1,314,733.6	31,512,085.6	95.99%
Cotton	518,404.6	677.4	415,570.7	102,833.9	19.84%
Sorghum	484,302.5	127.0	77,911.5	406,391.0	83.91%
Soybeans	14,401,870.9	2,342.8	1,437,236.6	12,964,634.3	90.02%
Wheat	8,377,934.5	1,287.4	789,750.4	7,588,184.1	90.57%

Table 27: Deviations from weighted DCV mean profit ($ millions)

		PDO+ TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO+ TAG- WPWP+	PDO- TAG+ WPWP+	PDO- TAG- WPWP-	PDO+ TAG+ WPWP+
	Neutral	33,763	35,129	-196,500	78,976	57,470	3,609	19,709	67,643
Corn	Nino	33,037	34,781	-194,673	78,192	56,867	4,009	19,764	67,039
	Nina	32,592	34,548	-194,294	77,824	56,861	4,038	20,475	67,034
	average	33,131	34,819	-195,156	78,330	57,066	3,885	19,983	67,239
	Neutral	1,447	-1,723	-411	1,185	422	249	156	560
Cotton	Nino	1,418	-1,741	-386	1,186	413	277	186	551
	Nina	1,392	-1,747	-373	1,202	410	281	216	548
	average	1,419	-1,737	-390	1,191	415	269	186	553
	Neutral	-1,135	49	-4,143	471	529	4,039	1,675	769
Sorghum	Nino	-1,154	121	-4,101	452	511	3,958	1,636	751
	Nina	-1,153	147	-4,133	456	518	3,971	1,595	758
	average	-1,147	106	-4,125	460	519	3,990	1,635	759
	Neutral	9,011	6,963	-61,094	31,960	13,557	20,625	-641	16,128
Soybeans	Nino	8,898	6,767	-60,806	31,917	13,616	20,632	-638	16,187
	Nina	8,621	6,824	-60,809	31,716	13,616	20,765	-404	16,186
	average	8,843	6,851	-60,903	31,864	13,596	20,674	-561	16,167
	Neutral	11,194	20,338	-49,769	30,196	14,151	-30,293	9,879	21,805
Wheat	Nino	10,935	19,976	-49,078	29,976	14,057	-30,011	9,860	21,711
	Nina	10,643	19,758	-48,588	29,613	13,936	-29,686	9,972	21,590
	average	10,924	20,024	-49,145	29,928	14,048	-29,997	9,903	21,702
	Neutral	54,279	60,757	-311,917	142,788	86,130	-1,771	30,778	106,905
TOTAL	Nino	53,133	59,905	-309,044	141,723	85,464	-1,135	30,807	106,240
	Nina	52,095	59,529	-308,196	140,811	85,341	-631	31,854	106,117
	average	53,169	60,063	-309,719	141,774	85,645	-1,179	31,146	106,421

Table 28: Transition probability matrix as forecasted information

Distribution of DCV phase combinations for next year: $\widehat{P}_{t+1}(DCV_t)$	DCV phase combinations for current year: DCV_t							
	PDO+ TAG- WPWP-	**PDO- TAG+ WPWP-**	**PDO- TAG- WPWP+**	**PDO+ TAG+ WPWP-**	**PDO+ TAG- WPWP+**	**PDO- TAG+ WPWP+**	**PDO- TAG- WPWP-**	**PDO+ TAG+ WPWP+**
PDO+ TAG- WPWP-	0.400	0.100	0.100	0.000	0.200	0.100	0.100	0.000
PDO- TAG+ WPWP-	0.231	0.615	0.000	0.000	0.077	0.000	0.000	0.077
PDO- TAG- WPWP+	0.000	0.000	0.600	0.100	0.000	0.100	0.000	0.200
PDO+ TAG+ WPWP+	0.000	0.000	0.000	0.000	0.000	0.500	0.500	0.000
PDO+ TAG- WPWP+	0.250	0.125	0.000	0.000	0.375	0.000	0.250	0.000
PDO- TAG+ WPWP+	0.000	0.000	0.143	0.000	0.000	0.571	0.143	0.143
PDO- TAG- WPWP-	0.167	0.000	0.167	0.167	0.167	0.167	0.167	0.000
PDO+ TAG+ WPWP+	0.000	0.333	0.167	0.000	0.167	0.000	0.000	0.333

Table 29: Average gain and loss from adaptation possibilities ($ millions)

		PDO+ TAG- WPWP-	PDO- TAG+ WPWP-	PDO- TAG- WPWP+	PDO+ TAG+ WPWP-	PDO+ TAG- WPWP+	PDO- TAG+ WPWP+	PDO- TAG- WPWP-	PDO+ TAG+ WPWP+	*DCV Weighted Average*
	Neutral	1,268.18	-10,584.40	19,133.20	77,124.34	-119.57	10,256.73	772.91	15,821.65	6,370.32
Corn	Nino	589.84	-4,443.94	16,626.52	63,435.43	-51.92	395.84	823.82	12,862.64	5,176.72
	Nina	909.13	-6,137.37	16,812.75	66,628.40	-47.33	3,088.60	1,014.65	13,539.39	5,434.04
	average	922.38	-7,055.24	17,524.16	69,062.72	-72.94	4,580.39	870.46	14,074.56	5,660.36
	Neutral	-77.52	345.76	48.35	646.23	1.30	87.69	65.85	127.97	116.99
Cotton	Nino	-66.02	280.99	53.97	697.85	0.51	90.29	73.16	113.59	107.54
	Nina	-65.53	279.04	55.79	717.05	0.57	97.56	73.36	116.85	109.37
	average	-69.69	301.93	52.70	687.04	0.79	91.85	70.79	119.47	111.30
	Neutral	-11.93	356.10	554.20	-21,620.25	3.92	-6,235.98	-2,556.93	291.15	-1,533.96
Sorghum	Nino	-301.77	-529.08	544.08	-21,524.05	-744.49	-6,199.65	-3,783.08	168.67	-1,980.04
	Nina	-386.11	63.38	-587.53	13,328.45	-45.80	-2,602.20	2,188.59	-1,895.93	-26.73
	average	-233.27	-36.53	170.25	-9,938.62	-262.12	-5,012.61	-1,383.81	-478.70	-1,180.24

	Neutral	334.82	-952.25	7,894.27	41,764.94	99.43	-648.31	3,334.13	7,931.15	3,438.76
Soybeans	Nino	277.98	-124.90	7,713.62	40,277.44	111.41	-3,580.61	3,390.60	7,183.98	3,087.95
	Nina	329.13	-404.70	7,336.26	36,886.88	106.36	-2,789.90	2,956.90	6,959.01	2,907.83
	average	313.97	-493.95	7,648.05	39,643.09	105.73	-2,339.61	3,227.21	7,358.05	3,144.85
	Neutral	-482.61	2,086.29	4,322.37	12,013.29	-69.42	7,882.48	-2,038.23	5,477.82	2,741.08
Wheat	Nino	-584.23	1,615.05	3,801.25	10,668.21	-111.73	9,208.53	-2,239.56	4,776.87	2,579.37
	Nina	-701.23	1,499.60	4,244.22	13,543.27	-108.06	10,026.05	-1,711.10	5,544.90	2,926.31
	average	-589.36	1,733.65	4,122.61	12,074.92	-96.40	9,039.02	-1,996.30	5,266.53	2,748.92
	Neutral	1,030.94	-8,748.50	31,952.39	109,928.55	-84.34	11,342.61	-422.27	29,649.74	11,133.19
TOTAL	Nino	-84.21	-3,201.88	28,739.44	93,554.89	-796.22	-85.61	-1,735.07	25,105.76	8,971.54
	Nina	85.39	-4,700.06	27,861.49	131,104.04	-94.26	7,820.11	4,522.40	24,264.22	11,350.83
	average	344.04	-5,550.15	29,517.77	111,529.16	-324.94	6,359.04	788.35	26,339.91	10,485.19

Note: The average gain and loss are estimated from the expected profits per acre multiplied by the expected harvested acre differences.

Figure 23: Agricultural adaptation comparison in percentage changes

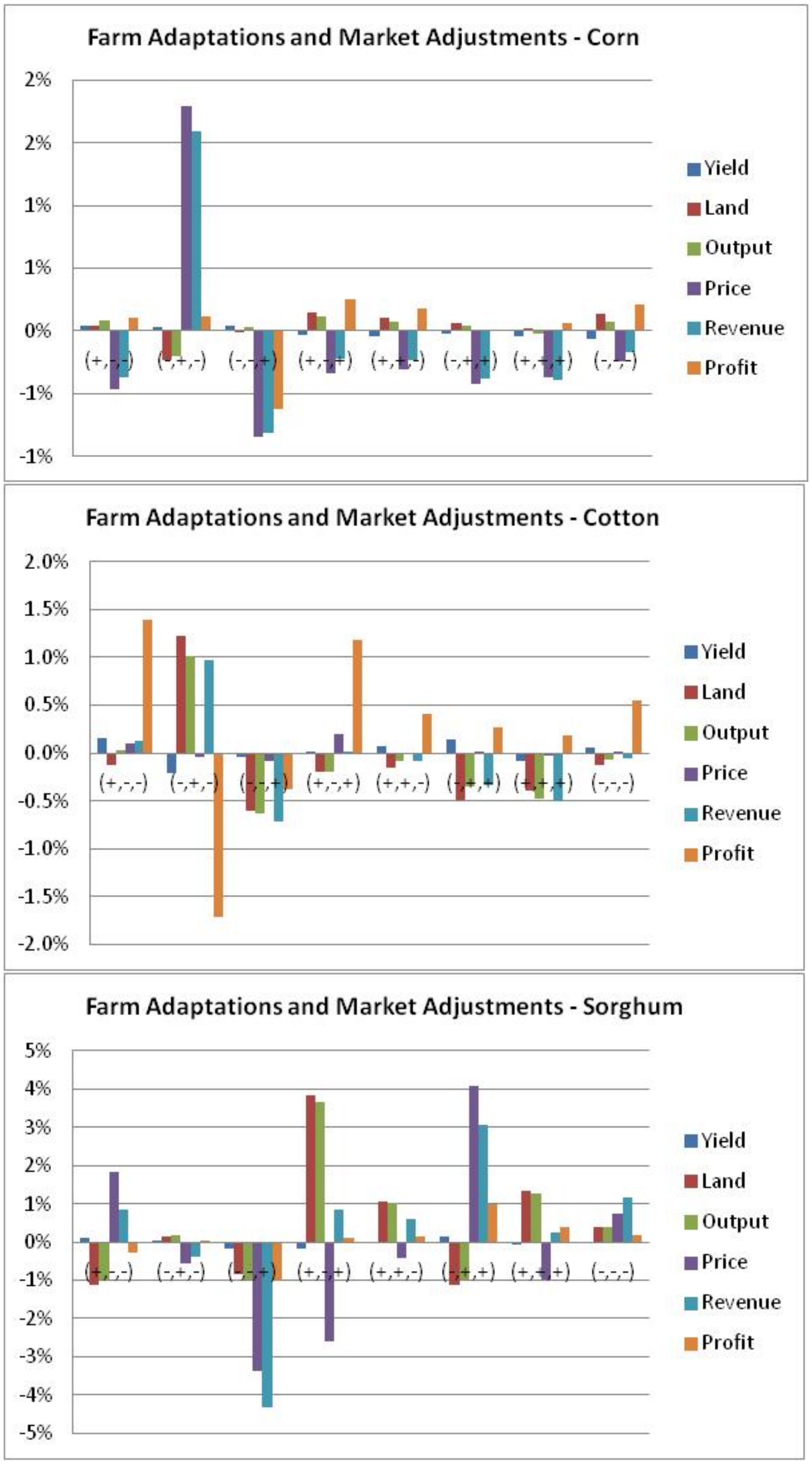
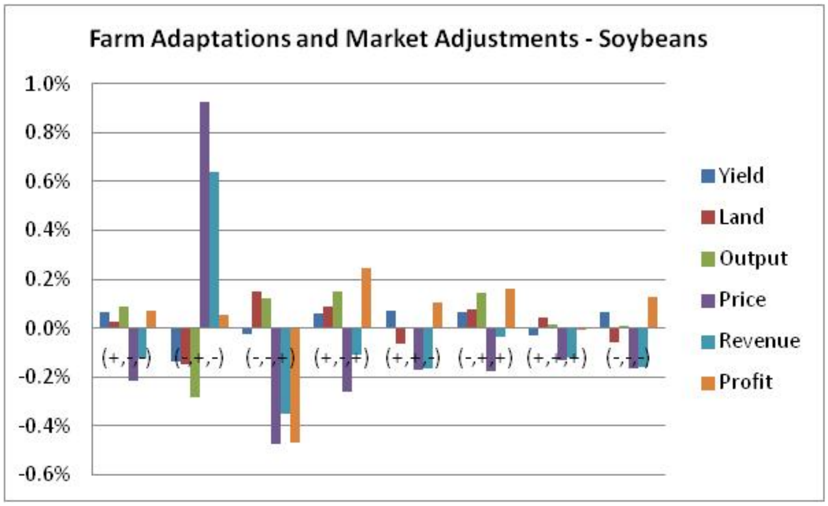


Figure 23: Agricultural adaptation comparison in percentage changes (cont'd)



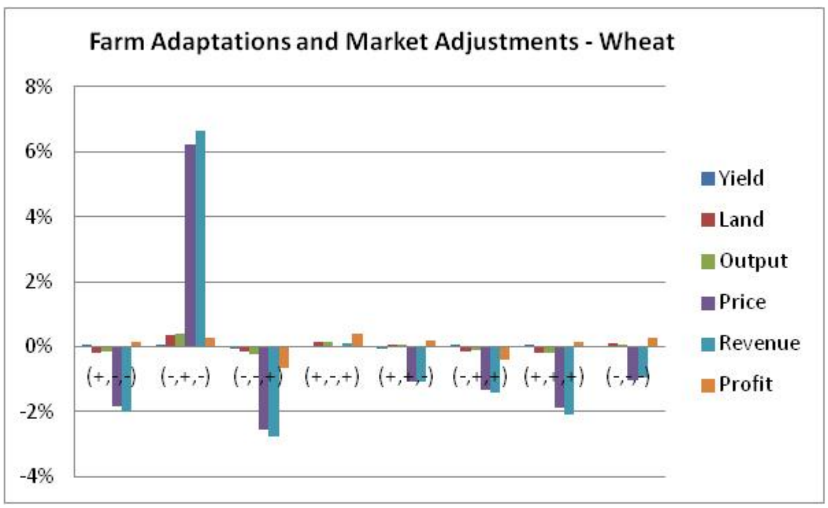


Table 30: Comparison of beverage categories used in prior studies on beverages

Study	Beverage Products	Types
Andreyeva et al. (2011)	Regular CSDs, diet CSDs, 100% fruit juice, fruit drinks, sports drinks, regular RTD tea, diet RTD tea, flavored/ enhanced water, energy drinks, RTD coffee, bottled water	11
Andreyeva et al. (2012)	CSDs, bottled water, 100% juice, fruit drinks, energy drinks and shots, sports drinks, RTD tea, flavored/enhanced water, RTD coffee, powdered non-alcoholic drinks	10
Dharmasena and Capps (2012)	Isotonics, regular CSDs, diet CSDs, high-fat milk, low-fat milk, fruit drinks, fruit juices, bottled water, coffee, tea	10
Zhen et al. (2011)	Regular CSDs, diet CSDs, whole milk, low-fat milk, bottled water, sports and energy drinks, fruit juice, coffee and tea, sugar sweetened fruit drink	9
Smith et al. (2010)	CSDs, diet CSDs, skim milk, low-fat milk, whole milk, juices, coffee/tea, bottled water	8
Pittman (2004)	Milk, CSDs, powdered soft drinks, isotonics, bottled water, fruit juices and fruit drinks, coffee, tea	8
Zheng and Kaiser (2008a)	Milk, juice, soft drinks, coffee/tea, bottled water	5
Fletcher et al. (2010)	Soft drinks, juice drink, whole milk, juice	4
Zheng and Kaiser (2008b)	Milk, juice, soft drinks, coffee/tea	4
Yen et al. (2004)	Soft drinks, milk, juice, coffee/tea	4
Kinnucan et al. (2001)	Soft drinks, milk, juice, coffee/tea	4
Dhar et al. (2003)	7-up, Coke, Dr. Pepper, Mt. Dew, Pepsi, RC Cola, Sprite, Private Label, and all-others	9

Note: CSDs - carbonated soft drinks, RTD – ready to drink.

Table 31: Number of loyalty cards by participation-transaction

Assistance Program Participation with Beverage-purchased Transaction Types	**Number of Households**
a. SNAP participants with SNAP payments	
b. SNAP participants with private payments	
c. Non-SNAP participants with private payments	
d. WIC participants with WIC payments	
(1) a. only	431
(2) b. only	250
(3) c. only	1,980
(4) d. only	3,137
(5) a. and b. only	2,095
(6) a. and c. only	n.a.
(7) a. and d. only	1,864
(8) b. and c. only	n.a.
(9) b. and d. only	1,593
(10) c. and d. only	11,861
(11) a., b., and c. only	n.a.
(12) a., b., and d. only	24,488
(13) b., c., and d. only	n.a.
(14) a., b., c. and d.	n.a.
Total loyalty cards with information on payment type percentages	47,699
Loyalty cards with *missing* information on payment type percentages	6
Total loyalty cards	47,705
Total SNAP participants with SNAP payments (1)+(5)+(7)+(12)	28,878
Total SNAP participants with private payments (2)+(5)+(9)+(12)	28,426
Total Non-SNAP participants with private payments (3)+(10)	13,841
Total WIC participants with WIC payments (4)+(7)+(9)+(10)+(12)	42,943

Note: n.a. occurs from impossibility in intersections of participation-transaction categories.

Table 32: Transaction data averages and standard deviations regarding purchases by beverage category and participant-transaction type

		SNAP Participants		Non-SNAP Participants	All Participants
		Purchases made using SNAP benefits	Purchases made using non-SNAP funds	Purchases made using non-SNAP funds	Purchases using WIC Payment
Expenditure	Regular Soda	8.21 (2.8)	6.43 (2.4)	6.69 (3.0)	
($)	Diet Soda	5.78 (3.0)	5.56 (2.4)	5.88 (2.5)	
	100% Juice	7.80 (3.0)	6.35 (2.2)	6.38 (1.9)	5.27 (2.2)
	Fruit Drinks	7.41 (2.7)	5.91 (5.6)	5.47 (2.1)	
	Energy Drinks	8.71 (8.2)	4.63 (4.1)	4.10 (4.9)	
	Sports Drinks	6.83 (4.0)	5.60 (4.4)	5.89 (3.8)	
	Bottled Water	5.94 (2.8)	5.03 (1.8)	5.47 (2.9)	
	Flavored Water	6.26 (3.9)	5.70 (3.7)	5.36 (3.8)	
	Ready to Drink Tea	5.93 (3.3)	5.41 (3.7)	5.48 (4.6)	
	Whole Milk	4.81 (1.7)	4.14 (1.0)	4.38 (1.6)	5.71 (2)
	2%, 1% or Skim Milk	4.91 (1.8)	4.52 (1.3)	4.97 (2.4)	5.95 (1.6)
Quantity	Regular Soda	340.7 (130.8)	283.9 (120.5)	303.0 (174.4)	
(oz)	Diet Soda	242.3 (121.3)	245.3 (120.1)	264.3 (123.6)	
	100% Juice	160.6 (54.7)	137.6 (43.2)	140.0 (43.8)	98.3 (35.4)
	Fruit Drinks	222.0 (91.4)	178.0 (178.3)	150.9 (65.8)	
	Energy Drinks	55.0 (52.5)	30.9 (26.9)	26.8 (30.1)	
	Sports Drinks	294.2 (311.2)	271.8 (336.9)	287.2 (318.9)	
	Bottled Water	464.4 (215.5)	402.3 (170.7)	416.9 (202.7)	
	Flavored Water	161.0 (132.5)	154.8 (112.6)	141.5 (123.1)	
	Ready to Drink Tea	201.2 (109.1)	189.4 (121.9)	186.0 (143)	
	Whole Milk	157.4 (52.7)	132.6 (32.9)	135.2 (42.3)	159.4 (46.4)
	2%, 1% or Skim Milk	139.8 (44.1)	131.2 (32.7)	143.1 (63.6)	164.9 (39.2)
Unit price	Regular Soda	2.94 (0.7)	2.94 (0.7)	2.91 (0.8)	
(cent/oz)	Diet Soda	2.71 (0.7)	2.68 (0.6)	2.64 (0.7)	
	100% Juice	5.57 (1.1)	5.39 (1.1)	5.36 (1)	6.04 (1.3)
	Fruit Drinks	4.41 (2.1)	4.28 (1.1)	4.50 (1.4)	
	Energy Drinks	18.44 (39.6)	23.04 (62.9)	19.68 (46.5)	
	Sports Drinks	3.55 (1.1)	3.45 (1.5)	3.43 (1.7)	

	Bottled Water	1.93 (1)	2.02 (0.8)	1.99 (0.9)	
	Flavored Water	4.72 (1.1)	4.56 (1.1)	4.68 (1.2)	
	Ready to Drink Tea	3.46 (1)	3.52 (1)	3.68 (1.3)	
	Whole Milk	3.25 (0.5)	3.39 (0.5)	3.51 (0.6)	3.77 (0.8)
	2%, 1% or Skim Milk	4.05 (1)	3.96 (0.8)	3.94 (0.8)	3.79 (0.7)
Budget	Regular Soda	0.117 (0.05)	0.112 (0.05)	0.113 (0.04)	
Share	Diet Soda	0.083 (0.04)	0.096 (0.04)	0.101 (0.05)	
	100% Juice	0.112 (0.05)	0.111 (0.04)	0.110 (0.04)	0.308 (0.08)
	Fruit Drinks	0.106 (0.04)	0.099 (0.05)	0.094 (0.04)	
	Energy Drinks	0.130 (0.08)	0.089 (0.06)	0.087 (0.07)	
	Sports Drinks	0.098 (0.05)	0.096 (0.05)	0.100 (0.05)	
	Bottled Water	0.085 (0.04)	0.089 (0.05)	0.093 (0.05)	
	Flavored Water	0.091 (0.05)	0.098 (0.05)	0.093 (0.06)	
	Ready to Drink Tea	0.086 (0.04)	0.093 (0.05)	0.092 (0.06)	
	Whole Milk	0.071 (0.04)	0.073 (0.03)	0.077 (0.04)	0.337 (0.07)
	2%, 1% or Skim Milk	0.072 (0.03)	0.080 (0.03)	0.086 (0.05)	0.357 (0.07)

Note: Authors' calculations from monthly scanner data of 58 stores in CT and MA (1/2009-6/2011).

Table 33: Parameter estimates for SNAP participants using SNAP payment benefits

EQUATIONS	Intercept	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	RTD Tea	Whole Milk	Lower-Fat Milk	Expend	Expend.^{2}	R^{2}
		Price Coefficients													
Regular Soda	0.386***	-0.026**											-0.035	-0.001	0.8948
	(<0.001)	(0.006)											(0.249)	(0.706)	
Diet Soda	-0.307**	0.015	-0.027										0.099***	-0.007***	0.8127
	(0.007)	(0.227)	(0.199)										(<0.001)	(<0.001)	
100% Juice	0.817***	-0.016	0.041*	-0.031									-0.136***	0.005*	0.8688
	(<0.001)	(0.287)	(0.030)	(0.309)									(<0.001)	(0.014)	
Fruit Drinks	0.581***	-0.014	0.034**	-0.058***	-0.026								-0.087***	0.004*	0.8909
	(<0.001)	(0.174)	(0.009)	(<0.001)	(0.091)								(<0.001)	(0.049)	
Energy Drinks	-0.172	0.012	0.015	-0.008	-0.005	-0.036***							-0.035	0.011***	0.7288
	(0.090)	(0.062)	(0.112)	(0.545)	(0.564)	(<0.001)							(0.127)	(<0.001)	
Sports Drinks	0.036	0.007	0.003	-0.002	0.013	-0.027***	-0.003						-0.015	0.004	0.7986
	(0.777)	(0.201)	(0.809)	(0.904)	(0.226)	(<0.001)	(0.668)						(0.641)	(0.082)	
Bottled Water	0.223*	-0.002	0.017	-0.021	-0.006	0.005	0.004	-0.005					-0.029	0.002	0.8405
	(0.023)	(0.694)	(0.09)	(0.096)	(0.53)	(0.359)	(0.390)	(0.425)					(0.252)	(0.451)	
Flavored Water	-0.065	0.016**	-0.006	0.011	0.007	-0.019***	-0.01**	-0.004	-0.007				0.004	0.003	0.7691
	(0.622)	(0.004)	(0.663)	(0.512)	(0.525)	(<0.001)	(0.007)	(0.405)	(0.166)				(0.914)	(0.236)	
Ready to Drink Tea	-0.467***	0.014	-0.047**	0.056**	0.043**	0.009	0.004	0.013	0.001	-0.050			0.125***	-0.007***	0.7887
	(<0.001)	(0.347)	(0.003)	(0.006)	(0.004)	(0.471)	(0.789)	(0.314)	(0.968)	(0.058)			(<0.001)	(<0.001)	
Whole Milk	0.083	-0.007	-0.017	0.008	-0.005	0.030***	0.006	-0.002	0.004	-0.011	0.010		0.036	-0.006***	0.8655
	(0.368)	(0.263)	(0.076)	(0.541)	(0.556)	(<0.001)	(0.308)	(0.714)	(0.485)	(0.323)	(0.188)		(0.136)	(<0.001)	
Lower-Fat Milk	-0.114	0.003	-0.029*	0.020	0.017	0.025***	0.006	0.001	0.007	-0.031*	-0.015*	-0.003	0.072**	-0.007***	
	(0.210)	(0.818)	(0.012)	(0.192)	(0.107)	(<0.001)	(0.507)	(0.916)	(0.478)	(0.047)	(0.047)	(0.860)	(0.003)	(<0.001)	

Note: Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 34: Parameter estimates for SNAP participants using private funds

EQUATIONS	Intercept	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	RTD Tea	Whole Milk	Lower-Fat Milk	Expend	Expend.^2	R^2
		Price Coefficients													
Regular Soda	0.054***	-0.033***											0.045***	-0.010***	0.8520
	(<0.001)	(<0.001)											(<0.001)	(<0.001)	
Diet Soda	0.101***	0.001	-0.015**										0.020**	-0.009***	0.8653
	(<0.001)	(0.8)	(0.006)										(0.002)	(<0.001)	
100% Juice	0.11***	0.005	-0.001	0.002									0.062***	-0.025***	0.9180
	(<0.001)	(0.221)	(0.851)	(0.734)									(<0.001)	(<0.001)	
Fruit Drinks	0.122***	-0.003	0.006	0.003	0.004								-0.008	-0.002	0.8280
	(<0.001)	(0.455)	(0.106)	(0.403)	(0.408)								(0.162)	(0.353)	
Energy Drinks	-0.019	0.001	-0.002	-0.002	-0.001	0.016***							-0.029***	0.020***	0.6548
	(0.089)	(0.891)	(0.453)	(0.423)	(0.833)	(<0.001)							(<0.001)	(<0.001)	
Sports Drinks	-0.002	-0.001	-0.002	0.002	0.005*	-0.002	0.002						0.043***	-0.001	0.7808
	(0.909)	(0.875)	(0.614)	(0.51)	(0.05)	(0.563)	(0.752)						(<0.001)	(0.951)	
Bottled Water	0.097***	0.004	0.001	-0.007*	-0.002	-0.004*	0.006*	0.010**					0.021***	-0.006***	0.8629
	(<0.001)	(0.224)	(0.796)	(0.016)	(0.654)	(0.029)	(0.017)	(0.006)					(<0.001)	(<0.001)	
Flavored Water	0.025*	0.009**	0.008*	0.004	-0.005	0.003	-0.007*	-0.003	-0.015**				0.007	0.008***	0.7931
	(0.018)	(0.006)	(0.02)	(0.271)	(0.109)	(0.189)	(0.032)	(0.43)	(0.002)				(0.401)	(<0.001)	
Ready to Drink Tea	0.036***	0.007*	0.005	-0.003	-0.001	-0.004	-0.008*	0.004	0.002	0.003			0.005	0.009***	0.7617
	(<0.001)	(0.04)	(0.123)	(0.492)	(0.764)	(0.074)	(0.011)	(0.19)	(0.691)	(0.523)			(0.535)	(<0.001)	
Whole Milk	0.134***	0.004	-0.006	-0.007	-0.004	0.002	-0.001	-0.007*	0.001	-0.004	0.022***		0.004	-0.012***	0.9405
	(<0.001)	(0.277)	(0.143)	(0.086)	(0.358)	(0.236)	(0.735)	(0.013)	(0.933)	(0.190)	(<0.001)		(0.466)	(<0.001)	
Lower-Fat Milk	0.346***	0.008*	0.004	0.003	-0.005	-0.009***	0.004	-0.004	0.005	-0.002	-0.002	-0.003	-0.167***	0.024***	
	(<0.001)	(0.033)	(0.372)	(0.462)	(3.215)	(<0.001)	(0.215)	(0.283)	(9.224)	(0.657)	(0.657)	(0.742)	(<0.001)	(<0.001)	

Note: Estimated coefficients with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 35: Parameter estimates for non-SNAP participants using private funds

EQUATIONS	Intercept	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	RTD Tea	Whole Milk	Lower-Fat Milk	Expend	Expend.^2	R^2
		Price Coefficients													
Regular Soda	0.365***	-0.029***											-0.006	-0.005**	0.8886
	(<0.001)	(<0.001)											(0.755)	(0.002)	
Diet Soda	-0.108*	0.004	-0.021*										0.058***	-0.005**	0.8502
	(0.014)	(0.579)	(0.011)										(<0.001)	(0.002)	
100% Juice	-0.313***	-0.008	-0.049***	-0.101***									0.183***	-0.018***	0.9067
	(<0.001)	(0.565)	(<0.001)	(<0.001)									(<0.001)	(<0.001)	
Fruit Drinks	0.135**	0.011*	0.015*	0.029*	-0.022**								-0.045**	0.006***	0.8493
	(0.004)	(0.043)	(0.015)	(0.025)	(0.008)								(0.005)	(<0.001)	
Energy Drinks	-0.081*	0.009***	0.004	0.007	-0.005	0.003							-0.004	0.004***	0.5511
	(0.016)	(<0.001)	(0.218)	(0.334)	(0.088)	(0.253)							(0.715)	(<0.001)	
Sports Drinks	-0.02	0.011**	0.005	0.023*	-0.011**	-0.01***	-0.001						-0.015	0.005***	0.7874
	(0.604)	(0.002)	(0.218)	(0.022)	(0.006)	(<0.001)	(0.98)						(0.257)	(<0.001)	
Bottled Water	0.997***	-0.008	0.057***	0.173***	-0.031*	0.001	-0.011	-0.27***					-0.252***	0.017***	0.8120
	(<0.001)	(0.654)	(<0.001)	(<0.001)	(0.047)	(0.978)	(0.411)	(<0.001)					(<0.001)	(<0.001)	
Flavored Water	0.114*	0.015*	0.024**	0.07***	-0.014*	-0.01*	-0.02***	-0.067***	-0.052***				-0.08***	0.012***	0.7330
	(0.027)	(0.037)	(0.002)	(<0.001)	(0.036)	(0.013)	(<0.001)	(<0.001)	(<0.001)				(<0.001)	(<0.001)	
RTD Tea	0.392***	0.01	0.028**	0.094***	-0.023*	-0.008	-0.015*	-0.114***	-0.053***	-0.08***			-0.131***	0.013***	0.7462
	(<0.001)	(0.295)	(0.004)	(<0.001)	(0.012)	(0.152)	(0.044)	(<0.001)	(<0.001)	(<0.001)			(<0.001)	(<0.001)	
Whole Milk	-0.238***	-0.008	-0.03***	-0.113***	0.026**	0.003	0.015	0.129***	0.056***	0.079***	-0.06***		0.143***	-0.014***	0.8259
	(<0.001)	(0.426)	(<0.001)	(<0.001)	(0.008)	(0.616)	(0.057)	(<0.001)	(<0.001)	(<0.001)	(<0.001)		(<0.001)	(<0.001)	
Lower-Fat Milk	-0.245***	-0.008	-0.034***	-0.123***	0.025*	0.006	0.014	0.14***	0.053***	0.081***	-0.09***	-0.064***	0.148***	-0.015***	
	(<0.001)	(0.472)	(<0.001)	(<0.001)	(0.016)	(0.317)	(0.08)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	

Note: Estimated coefficients with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 36: Parameter estimates for WIC payment benefits

EQUATIONS	Intercept	100% Juice	Whole Milk	Lower-Fat Milk	Expend	Expend.^2	R^2
		Price Coefficients					
100% Juice	1.865***	-0.579***			-0.545***	0.046***	0.9711
	(<0.001)	(<0.001)			(<0.001)	(<0.001)	
Whole Milk	0.009	0.13*	0.137***		0.164***	-0.017***	0.9760
	(0.945)	(0.033)	(<0.001)		(<0.001)	(<0.001)	
Lower-Fat Milk	-0.873***	0.45***	-0.266***	-0.184**	0.381***	-0.03***	
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)	

Note: Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 37: Parameter estimates for all WIC participants using all payment types

	Intercept	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	RTD Tea	Whole Milk	Lower-Fat Milk	Expend	Expend.^2	R^2
EQUATIONS		Price Coefficients													
Regular Soda	0.197***	-0.029***											-0.064***	0.011***	0.8971
	(<0.001)	(<0.001)											(<0.001)	(<0.001)	
Diet Soda	0.176***	-0.002	-0.014										-0.063***	0.01***	0.8297
	(<0.001)	(0.762)	(0.074)										(<0.001)	(<0.001)	
100% Juice	0.128***	-0.005	0.009	0.024***									0.048***	-0.024***	0.9079
	(<0.001)	(0.329)	(0.073)	(<0.001)									(<0.001)	(<0.001)	
Fruit Drinks	0.089***	0.004	0.007	0.005	0.005								0.007	-0.001	0.8693
	(<0.001)	(0.377)	(0.156)	(0.271)	(0.343)								(0.189)	(0.617)	
Energy Drinks	-0.051***	-0.002	0.001	-0.001	-0.002	0.009							-0.029***	0.032***	0.7969
	(<0.001)	(0.417)	(0.845)	(0.899)	(0.496)	(0.065)							(<0.001)	(<0.001)	
Sports Drinks	0.032***	0.007	-0.005	0.004	0.002	-0.006*	0.002						0.019***	0.003	0.8526
	(<0.001)	(0.061)	(0.227)	(0.199)	(0.671)	(0.015)	(0.697)						(<0.001)	(0.074)	
Bottled Water	0.113***	-0.005	-0.004	-0.005	0.006*	-0.004	0.002	0.013***					-0.004	-0.002	0.8690
	(<0.001)	(0.118)	(0.311)	(0.084)	(0.05)	(0.107)	(0.505)	(<0.001)					(0.465)	(0.21)	
Flavored Water	0.062***	0.013**	0.001	-0.009*	-0.004	0.003	-0.003	0.003	0.006				0.012*	0.001	0.8482
	(<0.001)	(0.002)	(0.98)	(0.016)	(0.314)	(0.347)	(0.443)	(0.391)	(0.257)				(0.027)	(0.794)	
RTD Tea	0.096***	0.004	0.009*	-0.005	0.002	-0.006*	0.005	-0.001	-0.006	0.002			-0.008	0.004*	0.8159
	(<0.001)	(0.422)	(0.048)	(0.19)	(0.678)	(0.025)	(0.169)	(0.971)	(0.153)	(0.855)			(0.203)	(0.045)	
Whole Milk	0.089***	0.01*	-0.005	-0.002	-0.009**	0.003	-0.003	-0.007**	0.002	-0.003	0.032***		0.028***	-0.014***	0.8753
	(<0.001)	(0.023)	(0.243)	(0.783)	(0.008)	(0.172)	(0.276)	(0.008)	(0.698)	(0.413)	(<0.001)		(<0.001)	(<0.001)	
Lower-Fat Milk	0.073	0.003	-0.029	0.02	0.017	0.025	0.006	0.001	0.007	-0.031	-0.015	-0.003	0.055	-0.019	
	(0.001)	(0.818)	(0.012)	(0.192)	(0.107)	(0.001)	(0.507)	(0.916)	(0.478)	(0.047)	(0.047)	(0.86)	(0.001)	(0.001)	

Note: Estimated coefficients with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 38: Estimated uncompensated own-price and cross-price elasticities and expenditure elasticities of SNAP participants using SNAP payment benefits

	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	Ready to Drink Tea	Whole Milk	Lower-Fat Milk	Expenditure Elasticity
Regular Soda	-1.081***	0.055	0.125**	0.066*	-0.007	0.047	0.036	0.102***	-0.004	0.005	0.023	0.616***
	(<0.001)	(0.076)	(0.002)	(0.022)	(0.783)	(0.052)	(0.21)	(<0.001)	(0.908)	(0.887)	(0.392)	(<0.001)
Diet Soda	-0.003	-0.882***	-0.143**	-0.004	0.055	-0.027	0.075*	-0.042	-0.009	-0.07	-0.043	1.094***
	(0.962)	(<0.001)	(0.008)	(0.929)	(0.111)	(0.415)	(0.016)	(0.268)	(0.844)	(0.058)	(0.203)	(<0.001)
100% Juice	0.167***	-0.029	-0.506***	-0.005	-0.117***	0.015	-0.027	0.038	-0.039	0.056	-0.034	0.449***
	(<0.001)	(0.4)	(<0.001)	(0.893)	(<0.001)	(0.592)	(0.418)	(0.227)	(0.257)	(0.069)	(0.227)	(<0.001)
Fruit Drinks	0.084**	0.051	-0.025	-0.892***	-0.08***	0.137***	0.06*	0.024	0.037	-0.054*	0.018	0.622***
	(0.005)	(0.073)	(0.492)	(<0.001)	(<0.001)	(<0.001)	(0.03)	(0.378)	(0.201)	(0.028)	(0.453)	(<0.001)
Energy Drinks	-0.155***	-0.094***	-0.222***	-0.181***	-0.880***	-0.154***	0.015	-0.097***	-0.119***	-0.062**	-0.09***	2.097***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.795)	(<0.001)	(<0.001)	(0.003)	(<0.001)	(<0.001)
Sports Drinks	-0.025	-0.071*	-0.059	0.094**	-0.111***	-0.987***	0.033	-0.074*	-0.053	-0.079***	-0.072**	1.423***
	(0.435)	(0.017)	(0.113)	(0.002)	(<0.001)	(<0.001)	(0.27)	(0.016)	(0.094)	(<0.001)	(0.002)	(<0.001)
Bottled Water	0.055	0.09**	-0.04	0.078**	0.051	0.054*	-1.012***	-0.057	-0.01	-0.033	-0.056*	0.873***
	(0.084)	(0.003)	(0.279)	(0.008)	(0.082)	(0.046)	(<0.001)	(0.057)	(0.749)	(0.192)	(0.019)	(<0.001)
Flavored Water	0.047	-0.095**	-0.036	-0.043	-0.049	-0.083*	-0.074*	-1.036***	0.005	-0.084**	-0.019	1.492***
	(0.235)	(0.01)	(0.438)	(0.239)	(0.179)	(0.014)	(0.049)	(<0.001)	(0.897)	(0.006)	(0.512)	(<0.001)
Ready to Drink Tea	-0.115**	-0.035	-0.175***	-0.043	0.021	-0.018	-0.033	0.051	-0.907***	-0.012	-0.029	1.308***
	(0.008)	(0.385)	(<0.001)	(0.291)	(0.565)	(0.609)	(0.305)	(0.181)	(<0.001)	(0.722)	(0.373)	(<0.001)
Whole Milk	0.018	0.015	0.044	-0.089*	0.114***	0.001	-0.043	0.008	0.111**	-0.616***	0.065	0.339***
	(0.719)	(0.736)	(0.431)	(0.029)	(<0.001)	(0.976)	(0.32)	(0.837)	(0.006)	(<0.001)	(0.105)	(<0.001)
Lower-Fat Milk	0.011	0.015	-0.126*	-0.008	0.075*	-0.002	-0.054	0.073*	0.061	0.031	-0.675***	0.598***
	(0.802)	(0.709)	(0.016)	(0.837)	(0.018)	(0.966)	(0.059)	(0.034)	(0.124)	(0.441)	(<0.001)	(<0.001)

Note: Estimated elasticities with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 39: Estimated uncompensated own-price and cross-price elasticities and expenditure elasticities of SNAP participants using non-SNAP payment funds

	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	Ready to Drink Tea	Whole Milk	Lower-Fat Milk	Expenditure Elasticity
Regular Soda	-1.048***	0.177***	0.401***	0.040	-0.117***	0.179***	0.169***	0.122**	0.096*	0.161***	-0.394***	0.202
	(<0.001)	(<0.001)	(<0.001)	(0.321)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.011)	(<0.001)	(<0.001)	(0.212)
Diet Soda	0.273***	-0.952***	0.389***	0.148***	-0.134***	0.172***	0.164***	0.128**	0.096*	0.105*	-0.373***	-0.033
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.021)	(0.034)	(<0.001)	(0.866)
100% Juice	0.733***	0.506***	0.056	0.257***	-0.333***	0.506***	0.352***	0.166*	0.102	0.354***	-1.070***	-1.678***
	(<0.001)	(<0.001)	(0.639)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.021)	(0.147)	(<0.001)	(<0.001)	(<0.001)
Fruit Drinks	0.029	0.111*	0.118	-0.928***	-0.026	0.087*	0.024	-0.041	0.002	0.012	-0.083	0.689***
	(0.641)	(0.034)	(0.162)	(<0.001)	(0.344)	(0.045)	(0.58)	(0.242)	(0.96)	(0.801)	(0.349)	(<0.001)
Energy Drinks	-1.008***	-0.789***	-1.546***	-0.378***	-0.300*	-0.717***	-0.667***	-0.159	-0.238*	-0.608***	1.303***	5.182***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.038)	(<0.001)	(<0.001)	(0.128)	(0.022)	(<0.001)	(<0.001)	(<0.001)
Sports Drinks	-0.028	-0.058	-0.028	-0.001	-0.017	-0.984***	0.037	-0.074*	-0.086**	-0.067	-0.116	1.426***
	(0.671)	(0.263)	(0.767)	(0.994)	(0.595)	(<0.001)	(0.392)	(0.023)	(0.007)	(0.112)	(0.234)	(<0.001)
Bottled Water	0.236***	0.153**	0.231**	0.048	-0.137***	0.209***	-0.779***	0.014	0.074*	0.043	-0.376***	0.273
	(<0.001)	(0.004)	(0.008)	(0.200)	(<0.001)	(<0.001)	(<0.001)	(0.71)	(0.044)	(0.321)	(<0.001)	(0.21)
Flavored Water	-0.203*	-0.153*	-0.419***	-0.186***	0.160***	-0.269***	-0.211***	-1.227***	-0.042	-0.205***	0.391***	2.387***
	(0.016)	(0.028)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.405)	(<0.001)	(<0.001)	(<0.001)
Ready to Drink Tea	-0.248**	-0.197**	-0.504***	-0.145**	0.096*	-0.292***	-0.153*	-0.051	-1.027***	-0.260***	0.358**	2.449***
	(0.003)	(0.004)	(<0.001)	(0.003)	(0.024)	(<0.001)	(0.011)	(0.303)	(<0.001)	(<0.001)	(0.002)	(<0.001)
Whole Milk	0.531***	0.304***	0.644***	0.151**	-0.187***	0.314***	0.207***	0.101	0.039	-0.401***	-0.639***	-1.102***
	(<0.001)	(<0.001)	(<0.001)	(0.009)	(<0.001)	(<0.001)	(<0.001)	(0.081)	(0.496)	(<0.001)	(<0.001)	(<0.001)
Lower-Fat Milk	-0.709***	-0.479***	-1.148***	-0.194*	0.311***	-0.589***	-0.524***	-0.096	-0.139	-0.372***	-0.772**	3.163***
	(<0.001)	(<0.001)	(<0.001)	(0.023)	(<0.001)	(<0.001)	(<0.001)	(0.312)	(0.136)	(<0.001)	(0.003)	(<0.001)

Note: Estimated elasticities with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 40: Estimated uncompensated own-price and cross-price elasticities and expenditure elasticities of non-SNAP participants using private payment funds

	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	Ready to Drink Tea	Whole Milk	Lower-Fat Milk	Expenditure Elasticity
Regular Soda	-1.012***	0.060	0.065	0.094**	0.021	0.048	0.125**	0.051	0.106**	0.025	0.034	0.346***
	(<0.001)	(0.093)	(0.069)	(0.010)	(0.221)	(0.070)	(0.005)	(0.149)	(0.004)	(0.285)	(0.190)	(<0.001)
Diet Soda	0.032	-1.093***	-0.108**	0.051	0.025	0.018	0.052	0.066	0.003	0.009	-0.027	0.974***
	(0.466)	(<0.001)	(0.003)	(0.156)	(0.115)	(0.477)	(0.094)	(0.058)	(0.941)	(0.725)	(0.281)	(<0.001)
100% Juice	0.161***	-0.055	-0.628***	-0.030	-0.023	0.059**	0.199***	0.050	0.045	-0.033	-0.090**	0.299***
	(<0.001)	(0.075)	(<0.001)	(0.346)	(0.132)	(0.007)	(<0.001)	(0.102)	(0.171)	(0.178)	(0.002)	(<0.001)
Fruit Drinks	-0.041	0.023	-0.126***	-1.133***	0.001	-0.047	0.013	0.052	-0.008	-0.058**	-0.077**	1.429***
	(0.347)	(0.513)	(<0.001)	(<0.001)	(0.956)	(0.090)	(0.671)	(0.155)	(0.834)	(0.007)	(0.002)	(<0.001)
Energy Drinks	-0.121***	-0.006	-0.100***	-0.040	-0.905***	-0.069**	-0.099*	-0.019	-0.075**	-0.105***	-0.073***	1.65***
	(<0.001)	(0.782)	(<0.001)	(0.109)	(<0.001)	(0.006)	(0.015)	(0.463)	(0.007)	(<0.001)	(<0.001)	(<0.001)
Sports Drinks	-0.089**	-0.015	-0.003	-0.078**	-0.046*	-0.948***	-0.096*	-0.108***	-0.078*	-0.031*	-0.045**	1.57***
	(0.010)	(0.575)	(0.909)	(0.010)	(0.018)	(<0.001)	(0.026)	(<0.001)	(0.018)	(0.038)	(0.010)	(<0.001)
Bottled Water	-0.004	0.054	0.068*	0.120***	0.034	0.029	-1.426***	0.065	0.078*	-0.014	0.061*	0.935***
	(0.933)	(0.084)	(0.045)	(<0.001)	(0.085)	(0.282)	(<0.001)	(0.057)	(0.037)	(0.530)	(0.014)	(<0.001)
Flavored Water	-0.161***	0.015	-0.046	0.005	-0.007	-0.114***	-0.132*	-1.176***	-0.152***	-0.014	-0.064*	1.900***
	(<0.001)	(0.683)	(0.200)	(0.902)	(0.758)	(<0.001)	(0.035)	(<0.001)	(<0.001)	(0.550)	(0.011)	(<0.001)
Ready to Drink Tea	-0.090	-0.036	-0.090*	-0.003	-0.011	-0.036	-0.063	-0.078	-1.187***	0.010	0.003	1.618***
	(0.056)	(0.327)	(0.016)	(0.943)	(0.633)	(0.279)	(0.253)	(0.054)	(<0.001)	(0.666)	(0.930)	(<0.001)
Whole Milk	0.166***	0.057	-0.037	0.014	-0.064***	0.025	0.158**	0.074*	0.144***	-0.726***	-0.024	0.159***
	(<0.001)	(0.069)	(0.344)	(0.655)	(<0.001)	(0.215)	(0.006)	(0.011)	(<0.001)	(<0.001)	(0.494)	(<0.001)
Lower-Fat Milk	0.164***	0.011	-0.116**	-0.007	-0.024	0.011	0.282***	0.016	0.129***	-0.025	-0.652***	0.212***
	(<0.001)	(0.736)	(0.003)	(0.838)	(0.115)	(0.624)	(<0.001)	(0.606)	(<0.001)	(0.420)	(<0.001)	(<0.001)

Note: Estimated elasticities with p-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 41: Estimated uncompensated own-price and cross-price elasticities and expenditure elasticities of WIC payment benefits

	100% Juice	Whole Milk	Lower-Fat Milk	Expenditure Elasticity
100% Juice	-0.202**	0.109***	-0.188***	0.994***
	(0.008)	(<0.001)	(<0.001)	(<0.001)
Whole Milk	-0.307***	-0.857***	-0.064***	0.913
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Lower-Fat Milk	-0.465***	-0.261***	-0.769***	1.088***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Note: Estimated elasticities with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 42: Estimated uncompensated own-price and cross-price elasticities and expenditure elasticities of all WIC participants using all payment types

	Regular Soda	Diet Soda	100% Juice	Fruit Drinks	Energy Drinks	Sports Drinks	Bottled Water	Flavored Water	Ready to Drink Tea	Whole Milk	Lower-Fat Milk	Expenditure Elasticity
Regular Soda	-1.102***	0.16**	-0.399***	-0.065	0.159***	-0.055	-0.123**	0.014	0.005	-0.121*	-0.284***	1.799***
	(<0.001)	(0.003)	(<0.001)	(0.164)	(<0.001)	(0.195)	(0.002)	(0.784)	(0.917)	(0.024)	(<0.001)	(<0.001)
Diet Soda	0.178**	-0.948***	-0.295**	-0.037	0.201***	-0.173***	-0.117*	-0.114*	0.075	-0.287***	-0.333***	1.837***
	(0.004)	(<0.001)	(0.002)	(0.51)	(<0.001)	(<0.001)	(0.013)	(0.049)	(0.171)	(<0.001)	(<0.001)	(<0.001)
100% Juice	-0.253***	-0.157*	0.245*	0.363***	-0.47***	0.338***	0.249***	0.229***	0.097	0.599***	0.748***	-1.947***
	(<0.001)	(0.027)	(0.031)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.138)	(<0.001)	(<0.001)	(<0.001)
Fruit Drinks	0.021	0.046	0.071	-0.944***	-0.032	0.023	0.063	-0.03	0.018	-0.078	-0.106	0.95***
	(0.643)	(0.309)	(0.344)	(<0.001)	(0.398)	(0.554)	(0.073)	(0.494)	(0.67)	(0.133)	(0.094)	(<0.001)
Energy Drinks	0.165**	0.227**	-1.228***	-0.417***	-0.365**	-0.41***	-0.415***	-0.371***	-0.247***	-0.72***	-1.037***	4.767***
	(0.01)	(0.002)	(<0.001)	(<0.001)	(0.003)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Sports Drinks	0.042	-0.062	-0.131	-0.051	0.01	-1.031***	-0.053	-0.083*	0.007	-0.135**	-0.178**	1.655***
	(0.267)	(0.113)	(0.083)	(0.2)	(0.803)	(<0.001)	(0.117)	(0.047)	(0.852)	(0.007)	(0.007)	(<0.001)
Bottled Water	-0.063	-0.047	0.04	0.102*	-0.083*	0.048	-0.807***	0.063	0.018	-0.02	0.092	0.664***
	(0.118)	(0.253)	(0.585)	(0.011)	(0.028)	(0.199)	(<0.001)	(0.131)	(0.636)	(0.681)	(0.135)	(<0.001)
Flavored Water	0.113*	-0.02	-0.134	-0.056	0.039	-0.035	0.005	-0.953***	-0.072	-0.012	-0.074	1.194***
	(0.013)	(0.672)	(0.094)	(0.208)	(0.328)	(0.399)	(0.896)	(<0.001)	(0.088)	(0.837)	(0.271)	(<0.001)
Ready to Drink Tea	0.075	0.143**	-0.231*	-0.038	0.015	-0.001	-0.053	-0.117*	-1.014***	-0.136*	-0.158*	1.509***
	(0.14)	(0.007)	(0.011)	(0.454)	(0.75)	(0.996)	(0.214)	(0.026)	(<0.001)	(0.026)	(0.039)	(<0.001)
Whole Milk	-0.03	-0.267***	0.815***	0.137*	-0.347***	0.207***	0.15**	0.28***	0.081	-0.044	0.478***	-1.426***
	(0.682)	(<0.001)	(<0.001)	(0.032)	(<0.001)	(<0.001)	(0.01)	(<0.001)	(0.211)	(0.669)	(<0.001)	(<0.001)
Lower-Fat Milk	-0.189**	-0.251***	0.852***	0.159*	-0.433***	0.268***	0.266***	0.271***	0.136*	0.393***	0.481***	-1.951***
	(0.007)	(<0.001)	(<0.001)	(0.012)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.045)	(<0.001)	(<0.001)	(<0.001)

Note: Estimated elasticities with *p*-values in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table 43: Effects of half-cent per ounce tax on monthly consumption (in ounce)

	All WIC Participants using All Payment Types			(a) SNAP Participants using SNAP Benefits			(b) SNAP Participants using Private Fund			(c) Non-SNAP Participants using Private Fund		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
Regular Soda	-57.76	-2.65	-60.41	-62.61	8.21	-54.40	-50.71	15.54	-35.17	-52.72	11.39	-41.33
Diet Soda		1.22	1.22		-2.10	-2.10		27.77	27.77		5.71	5.71
100% Juice		10.16	10.16		4.04	4.04		34.92	34.92		6.12	6.12
Fruit Drinks	-20.07	0.98	-19.09	-22.48	8.67	-13.81	-19.27	2.27	-17.01	-19.00	-1.41	-20.40
Energy Drinks	-0.52	-8.36	-8.88	-1.31	-5.27	-6.58	-0.20	-11.46	-11.66	-0.61	-1.26	-1.88
Sports Drinks	-43.85	-1.97	-45.82	-40.93	-3.47	-44.40	-38.81	-6.90	-45.70	-39.71	-13.50	-53.21
Bottled Water		6.41	6.41		9.10	9.10		34.20	34.20		14.60	14.60
Flavored Water	-18.71	-0.24	-18.95	-17.68	-1.48	-19.16	-20.84	-15.10	-35.94	-17.79	-9.10	-26.89
Ready to Drink Tea	-30.44	-0.89	-31.33	-26.37	-4.16	-30.54	-27.64	-19.86	-47.49	-30.04	-5.48	-35.51
Whole Milk		10.70	10.70		2.03	2.03		22.01	22.01		8.03	8.03
Lower-Fat Milk		8.84	8.84		2.69	2.69		-33.10	-33.10		6.78	6.78

Note: The estimated impacts are evaluated by sample average of price indices and quantity purchases, given the estimated own- and cross-price elasticities.

Table 44: Effects of half-cent per ounce tax on monthly consumption (in calorie)

	All WIC Participants using All Payment Types			(a) SNAP Participants using SNAP Benefits			(b) SNAP Participants using Private Fund			(c) Non-SNAP Participants using Private Fund		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
Regular Soda	-731.66	-33.59	-765.26	-793.02	103.97	-689.05	-642.29	196.83	-445.46	-667.76	144.24	-523.52
Diet Soda		0.41	0.41		-0.70	-0.70		9.26	9.26		1.90	1.90
100% Juice		146.02	146.02		58.01	58.01		501.94	501.94		87.99	87.99
Fruit Drinks	-309.62	15.14	-294.48	-346.79	133.77	-213.02	-297.29	34.98	-262.31	-293.04	-21.71	-314.75
Energy Drinks	-6.78	-109.50	-116.28	-17.18	-69.01	-86.19	-2.63	-150.10	-152.73	-8.05	-16.56	-24.61
Sports Drinks	-345.32	-15.52	-360.84	-322.32	-27.35	-349.67	-305.62	-54.31	-359.92	-312.69	-106.33	-419.02
Bottled Water		0.00	0.00									
Flavored Water	-231.54	-2.99	-234.54	-218.80	-18.26	-237.06	-257.84	-186.92	-444.76	-220.14	-112.57	-332.71
Ready to Drink Tea	-334.87	-9.78	-344.65	-290.09	-45.80	-335.89	-304.00	-218.43	-522.43	-330.39	-60.26	-390.65
Whole Milk		200.67	200.67		38.07	38.07		412.69	412.69		150.58	150.58
Lower-Fat Milk		113.88	113.88		34.65	34.65		-426.15	-426.15		87.31	87.31

Note: The estimated impacts are evaluated by sample average of price indices and quantity purchases, given the estimated own- and cross-price elasticities. The calories of beverages are from USDA, Agricultural Research Service's Nutrient Data Laboratory.

Table 45: Potential consequences of taxes on SSBs to reduce consumption

	All WIC Participants using All Payment Types		(a) SNAP Participants using SNAP Benefits		(b) SNAP Participants using Private Fund		(c) Non-SNAP Participants using Private Fund	
Tax rate	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz
Monthly caloric-reduction	1,655.07	3,310.15	1,780.85	3,561.71	1,689.87	3,379.74	1,677.47	3,354.94
Percentage reduction	7.7%	15.3%	8.1%	16.1%	8.8%	17.7%	8.8%	17.6%
Annual consumption reduction (12 oz can of Coca Cola)	130	260	140	280	133	266	132	264

Note: The calories of beverages are from USDA, Agricultural Research Service's Nutrient Data Laboratory. Percentage reduction is based on the average monthly consumed by participant-transaction group.

Table 46: Tax incidence per loyalty card by beverage ($)

	All WIC Participants using All Payment Types		(a) SNAP Participants using SNAP Benefits		(b) SNAP Participants using Private Fund		(c) Non-SNAP Participants using Private Fund	
Tax rate	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz
Regular Soda	1.28	1.96	1.43	2.32	1.24	2.13	1.31	2.20
Diet Soda								
100% Juice								
Fruit Drinks	0.90	1.60	1.04	1.94	0.80	1.44	0.65	1.10
Energy Drinks	0.23	0.38	0.24	0.42	0.10	0.08	0.12	0.23
Sports Drinks	1.29	2.13	1.25	2.05	1.13	1.80	1.17	1.81
Bottled Water								
Flavored Water	0.81	1.42	0.71	1.23	0.59	0.83	0.57	0.88
Ready to Drink Tea	0.91	1.51	0.85	1.40	0.71	0.94	0.75	1.15
Whole Milk								
Lower-Fat Milk								

Note: The estimated impacts are evaluated by sample average of price indices and quantity purchases, given the estimated own- and cross-price elasticities. The calories of beverages are from USDA, Agricultural Research Service's Nutrient Data Laboratory. Reduction in consumption is based on the estimated impacts on average monthly consume by each participant-transaction group.

Table 47: Tax burden per participant and tax revenue

	All WIC Participants using All Payment Types		(a) SNAP Participants using SNAP Benefits		(b) SNAP Participants using Private Fund		(c) Non-SNAP Participants using Private Fund	
Tax rate	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz	¢0.5/oz	¢1/oz
Per participant burden/month ($)	5.42	9.00	5.52	9.36	4.58	7.23	4.58	7.37
% of monthly SNAP benefit	2.2%	3.7%	2.3%	3.9%	1.9%	3.0%	1.9%	3.0%
Annual tax revenue ($)			48,512,237.04	82,194,617.98	40,197,123.17	63,449,057.05	9,573,616.50	15,400,772.11
Total annual tax revenue from (a) + (b) + (c) ($)							98,282,976.71	161,044,447.14

Note: The estimated impacts are evaluated by sample average of price indices and quantity purchases, given the estimated own- and cross-price elasticities. The annual tax revenue from (a), (b), and (c) are mutually exclusive at the beverage-purchased transaction level

APPENDIX B

Table A1: Frequency of DCV and ENSO events from 1950-2012

	Total	Percentage
PDO positive phase combination	26	41.3%
TAG positive phase combination	35	55.6%
WPWP positive phase combination	26	41.3%
PDO+, TAG-, WPWP-	10	15.9%
PDO-, TAG+, WPWP-	13	20.6%
PDO-, TAG-, WPWP+	10	15.9%
PDO+, TAG+, WPWP-	8	12.7%
PDO+, TAG-, WPWP+	2	3.2%
PDO-, TAG+, WPWP+	8	12.7%
PDO+, TAG+, WPWP+	6	9.5%
PDO-, TAG-, WPWP-	6	9.5%
El Niño	21	33.3%
La Niña	21	33.3%
Neutral	21	33.3%

Note: N=63 years where total of DCV equal to 100%. Same as DCV combinations and ENSO events.

Table A2: Statistics on annual weather variables from 1950-2012

	N	Mean	S.D.	Min	Max
United States					
Temperature	3,024	52.18	7.68	35.03	72.58
Precipitation		36.14	15.02	5.37	80.58
PDSI		0.22	2.03	-6.85	7.82
Day Temp>90°		35	29	0	142
Day Precip>90		64	21	8	135
Central					
Temperature	504	48.28	4.76	37.26	58.50
Precipitation		35.72	7.06	15.75	57.34
PDSI		0.56	1.87	-6.84	6.10
Day Temp>90°		17	16	0	86
Day Precip>90		69	11	37	123
Mountain					
Temperature	504	48.36	5.96	38.31	62.59
Precipitation		13.54	3.68	5.37	24.88
PDSI		-0.24	2.40	-6.07	7.05
Day Temp>90°		47	26	3	142
Day Precip>90		33	10	8	63
North East					
Temperature	693	48.39	4.54	39.18	58.81
Precipitation		44.58	6.97	27.59	69.60
PDSI		0.34	1.77	-4.53	6.07
Day Temp>90°		11	10	0	55
Day Precip>90		79	12	54	135
Northern Plains					
Temperature	252	47.15	5.47	35.03	57.82
Precipitation		22.14	5.57	11.50	41.50
PDSI		0.93	2.65	-6.85	7.82

Day Temp>90°		38	19	5	107
Day Precip>90		44	12	20	81
Pacific					
Temperature	189	51.92	5.31	44.85	61.05
Precipitation		29.30	8.78	11.87	49.20
PDSI		-0.08	1.82	-3.78	6.68
Day Temp>90°		10	9	0	39
Day Precip>90		74	19	38	121
South East					
Temperature	567	59.92	5.41	49.62	72.58
Precipitation		49.70	7.81	30.99	76.23
PDSI		0.08	1.69	-4.64	5.07
Day Temp>90°		50	25	1	116
Day Precip>90		75	10	50	107
Southern Plains					
Temperature	315	63.10	2.78	57.47	68.77
Precipitation		45.29	14.32	15.18	80.58
PDSI		0.02	2.02	-6.20	5.31
Day Temp>90°		79	22	21	138
Day Precip>90		61	17	22	98

Note: There are 48 US States which 8 Central states, 8 Mountain states, 11 North East states, 4 North - Plains states, 3 Pacific states, 9 South East states, and 5 Southern Plains. The weather variables are annual average temperatures (degrees Fahrenheit), total precipitation (inches), and Palmer Drought Severity Index (PDSI), number of days with maximum temperature greater than or equal 90° F, and number of days with greater than or equal to 1 inch of precipitation.

Table A3: Weather stations used for temperature and precipitation data

State	Station ID	Station
Alabama	USW00013876	BIRMINGHAM AIRPORT, AL
Arizona	USW00093026	DOUGLAS BISBEE INL AIRPORT, AZ
Arkansas	USC00033862	KEO, AR
California	USW00024213	EUREKA WEATHER FORECAST OFFICE WOODLEY ISLAND, CA
Colorado	USC00054452	KASSLER, CO
Connecticut	USW00094702	BRIDGEPORT SIKORSKY MEMORIAL AIRPORT, CT
Delaware	USC00079605	WILMNGTON PORTER RSV, DE
Florida	USW00013899	PENSACOLA REGIONAL AIRPORT, FL
Georgia	USW00093842	COLUMBUS METROPOLITAN AIRPORT, GA
Idaho	USW00024149	LEWISTON NEZ PERCE CO AIRPORT, ID
Illinois	USW00093822	SPRINGFIELD ABRAHAM LINCOLN CAPITAL AIRPORT, IL
Indiana	USW00093819	INDIANAPOLIS INTERNATIONAL AIRPORT, IN
Iowa	USC00131257	CASCADE, IA
Kansas	USC00146242	PARSONS 2 NW, KS
Kentucky	USW00093814	CINCINNATI NORTHERN KY AIRPORT, KY
Louisiana	USC00164700	JENNINGS, LA
Maine	USW00014764	PORTLAND INTERNATIONAL JETPORT, ME
Maryland	USW00093720	SALISBURY WICOMICO REGIONAL AIRPORT, MD
Massachusetts	USW00014739	BOSTON LOGAN INTERNATIONAL AIRPORT, MA
Michigan	USW00014833	JACKSON REYNOLDS FIELD, MI
Minnesota	USC00213303	GRAND RAPIDS FRS LAB, MN
Mississippi	USW00013865	MERIDIAN KEY FIELD, MS
Missouri	USW00013995	SPRINGFIELD REGIONAL AIRPORT, MO
Montana	USW00024144	HELENA REGIONAL AIRPORT, MT
Nebraska	USC00254455	KINGSLEY DAM, NE
Nevada	USW00023185	RENO TAHOE INTERNATIONAL AIRPORT, NV
New Hampshire	USC00276818	PINKHAM NOTCH, NH
New Jersey	USC00281582	CHARLOTTEBURG RESERVOIR, NJ
New Mexico	USW00023050	ALBUQUERQUE INTERNATIONAL AIRPORT, NM
New York	USW00014735	ALBANY AIRPORT, NY
North Carolina	USW00013722	RALEIGH DURHAM INTERNATIONAL AIRPORT, NC
North Dakota	USW00024011	BISMARCK MUNICIPAL AIRPORT, ND
Ohio	USW00014820	CLEVELAND HOPKINS INTERNATIONAL AIRPORT, OH
Oklahoma	USW00013969	PONCA CITY MUNICIPAL AIRPORT, OK
Oregon	USW00024229	PORTLAND INTERNATIONAL AIRPORT, OR

Pennsylvania	USW00013739	PHILADELPHIA INTERNATIONAL AIRPORT, PA
Rhode island	USW00014765	PROVIDENCE T F GREEN STATE AIRPORT, RI
South Carolina	USW00013883	COLUMBIA METROPOLITAN AIRPORT, SC
South Dakota	USC00396054	NEWELL, SD
Tennessee	USW00013882	CHATTANOOGA LOVELL FIELD AIRPORT, TN
Texas	USW00023007	CHILDRESS MUNICIPAL AIRPORT, TX
Utah	USW00093129	CEDAR CITY MUNICIPAL AIRPORT, UT
Vermont	USC00431243	CAVENDISH, VT
Virginia	USW00013743	WASHINGTON REAGAN NATIONAL AIRPORT, VA
Washington	USW00024157	SPOKANE INTERNATIONAL AIRPORT, WA
West Virginia	USW00013734	MARTINSBURG EASTERN WV REGIONAL AIRPORT, WV
Wisconsin	USC00473058	GERMANTOWN, WI
Wyoming	USW00024029	SHERIDAN CO AIRPORT, WY

Note: All weather stations with complete coverage of data availability for 48 states in 1950-2012.

APPENDIX C

Centered parameterization

This section describes a one-to-one correspondence between direct parameterization and centered parameterization that exists in the univariate skew-normal distribution. We obtain the estimated parameters with direct parameterized estimation and then calculate the statistical moments from these parameters. So after obtaining estimates in the direct parameterization metric, one can use the closed forms and the delta method to obtain respective estimates of mean, variance, skewness, and their standard errors in the direct parameterization metric. From the univariate skew-normal distribution's direct parameterization as described in the methodology part, we derive the mean, standard deviation, and skewness from the centered parameterization. The use of centered parameterization is advantageous from both interpretation and inferential standpoints. As the mean μ of a skewed random variable is not the same as the location parameter ξ, $E(\varepsilon) \neq 0$ (unless $\alpha = 0$) unlike the normal linear regression model. The mean $E(\varepsilon) = \sqrt{2/\pi}\omega\delta$ for the skew-normal regression, where $\delta = \alpha / \sqrt{1+\alpha^2}$. Then $E(y) = \xi + E(\varepsilon)$.

Consider the following decomposition for centered parameterization of Y:

(a) $$Y = \xi + \omega Z = \mu + \sigma(Y - \mu_z) / \sigma_z$$

where $\mu_z = E(Z) = \sqrt{2/\pi}\delta$, $\sigma_z^2 = Var(Z) = 1 - 2\delta^2/\pi$, and $\delta = \alpha/\sqrt{1+\alpha^2}$. Therefore, we have the mean $\mu = E(Y) = \xi + \omega\mu_z$, variance $\sigma^2 = Var(Y) = \omega^2(1-\mu_z^2)$, and skewness $\gamma = Skew(Y) = (4-\pi)sign(\alpha)(\mu_z/\sigma_z^2)^3/2$ which characterize the crop yield distribution up to the third moments.

Log-skew-normal estimation for outputs and revenues

We use the log-skew-normal distribution approach for outputs and revenues. This is an extension for skew-normal distribution with positive support for the variable which is skew-normal distributed after the logarithmic transformation.

Essentially, this is analogous with the commonly known log-normal distribution. Marchenko and Genton (2010) analyzed the properties and provided the moments of the univariate log-skew-normal as the following.

$$E(Y) = 2\exp(\xi + \omega^2/2)\Phi(\alpha\omega/(1+\alpha^2)^{1/2})$$

$$E(Y^2) = 2\exp(2\xi + 2\omega^2)\Phi(2\alpha\omega/(1+\alpha^2)^{1/2})$$

$$E(Y^3) = 2\exp(3\xi + 4.5\omega^2)\Phi(3\alpha\omega/(1+\alpha^2)^{1/2}),$$

such that, we could calculate mean, variance, and skewness of outputs and revenues from the above moment formulas with their standard closed forms, such as $Var(Y) = E(Y^2) - (E(Y))^2$ or $Skew(Y) = (E(Y^2) - 3\mu\sigma^2 - \mu^3)/\sigma^3$. We estimate by the delta method which is an approximation method using Taylor expansion.

Zero-inflated Poisson regression

Zero-inflated Poisson (ZIP) regression is used to model count data that has the zero counts inflation. Further, theory suggests that the excess zeros are generated by the separated process from the count values and that the inflated zeros can be modeled independently. Thus, the ZIP model has two parts, a Poisson count model and the logit model for predicting excess zeros. The response variable $Z = (Z_1, \ldots, Z_n)$ are independent, and have the following form:

$$Z_i \sim \begin{cases} 0 & ; p_i \\ Poisson(\lambda_i) & ; 1 - p_i \end{cases} \tag{b}$$

with the Poisson mean $\lambda = (\lambda_1, \ldots, \lambda_n)$ satisfies $\log(\lambda) = X\beta$ and the probability parameters $p = (p_1, \ldots, p_n)$ satisfies $logit(p) = \log(\frac{p}{1-p}) = X_p\gamma$ for covariates X and X_p.

Clearly, $E[Z_i \mid X_i] = (1 - p_i)\lambda_i$ and $Var[Z_i \mid X_i] = (1 - p_i)(\lambda_i + p_i\lambda_i^2$. So this framework accommodates over-dispersion of the zero data (if $p_i > 0$). When $p_i = 0$, this model is reduced to the standard Poisson regression model. The zero-inflated negative binomial model also shares this structural pattern with different distribution on the average mean equation (b).